Modeling and Control of an Aircraft System

(for Aerospace Applications)

Thesis submitted in partial fulfillment of the requirements for the degree of

Master of Technology

in

Electrical Engineering

(Specialization: Control & Automation)

by

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Certificate

This is to certify that the work in the thesis entitled ***Modeling and Control of an Aircraft System (for Aerospace Applications)*** by ***Ankit Gupta*** is a record of an original research work carried out by him under my supervision and guidance in partial fulfillment of the requirements for the award of the degree of Master of Technology with the specialization of **Control** & **Automation** in the department of **Electrical Engineering**, National Institute of Technology Rourkela. Neither this thesis nor any part of it has been submitted for any degree or academic award elsewhere.

Place: NIT Rourkela
Date: May 2015

Dr. Bidyadhar Subudhi
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Ankit Gupta
213EE3305

Abstract

This thesis presents design of a basic mathematical model of an aircraft system. The proposed model is implemented on a nonlinear aircraft system with six degree of freedom, which is linearized into lateral and longitudinal flight dynamics mode of an aircraft system. To achieve the specific transient performances of the both longitudinal and lateral flight dynamics mode, a model predictive control strategy is designed. The proposed model predictive control scheme is implemented on the developed aircraft model with six degree of freedom. Simulation were pursuit using Matlab / Simulink. The result obtained envisages that the aircraft system using the proposed model predictive controller achieves the good transient performances.

This thesis also presents a design of Kalman filter based diagnostic technique for deficiency identification and segregation of sensors and actuators in an air ship gas turbofan engine. A mathematical model of a two shaft turbofan engine is develop in Matlab / Simulink. The proposed Kalman filter based diagnostic technique consist of a bank of Kalman filters used to recognize and separate sensor flaw. Each of the Kalman filter is composed in view of a particular speculation for identifying a particular sensor issues. At the point when an issue happen, all channel aside from the one utilizing the right speculation will deliver huge estimation slip, from which a particular deficiency is secluded. The failure in the sensor influence the attributes of the residual signal of the Kalman filter. The proposed diagnostic technique is implemented on the developed two shaft turbofan engine. Simulation were pursuit utilizing Matlab / Simulink.

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Chapter 1

Introduction

Chapter 1

Introduction

Nowadays, the accident in aircraft increasing and according to NTSB data [1], aircraft system malfunctions were related to 52% of the accident whereas propulsion system malfunctions cause 36% of the accident. The increasing complexity of aerospace system such as jet engines and cost reduction measure, which affected aircraft and engine maintenance operators are increasingly demanding more intelligence, automation capabilities and functionalities for diagnosis and system malfunctions. Therefore, it is important to identify the occurrence of faulty conditions in the aircraft and to isolate these faults. By enabling the fault diagnosis strategy for aircraft engine can altogether enhance the flight safety.

1.1 Background of the thesis

As 52% of the flight accident are related to aircraft system malfunction so it is significant to understand the basic model of an aircraft, which includes aircraft dynamics, forces and moments, wind turbulence etc. The aircraft model can easily be understood by understanding the dynamic equations of motion of aircraft. Since the aircraft model is highly nonlinear, therefore it is also required to convert it in a linear model.

A flight accident can cost the human lives as well as money, therefore it is necessary to design a controller, which achieves the specific performances of the aircraft model. A name suggest, model predictive control strategy is a control strategy based on models,which can easily handle basic changes,for example, failure actuator and sensor and system parameters changes by adjusting the control strategy on a specimen by test premise. Principle of receding horizon, is an important feature of model predictive control strategy, which optimized current state by considering the future state into account.

A flight accident can also occur due to propulsion system malfunction, which covers 36% of the flight accident. A fault diagnosis scheme for aircraft engine signifies the fault identification and its seclusion. Fault identification and isolation scheme play an essential part in upgrading the safety, reliability and minimizing the working expensive of propulsion system of the aircraft. Nonetheless, accomplishing the fault identification and its seclusion with high reliability is a testing issue, That is why different methodology have been presented in the aircraft control literature.

Some of the approaches used in fault detection and isolation scheme are Kalman filtering, neural networks and hybrid diagnosis. Numerous current fault identify and seclusion scheme are taking into account the suspicion that the system shows linear nature in the surrounding of the operating points at the steady state. Accordingly, diagnostic schemes based on linearization are generally utilized. Since the dynamics of the aircraft engine are exceedingly nonlinear, therefore traditional linear model Kalman filter method, subjected to linear uncertainties is used.

1.2 Literature Review for the thesis

The basic model of aircraft is easily understood by mathematical modelling of the aircraft. M.V. Cook discuss about a linear system approach to aircraft stability and control in his book Flight Dynamic Principles [5]. D. Caughey gives the introduction to the aircraft modelling, stability and control [3]. He presents various views on implication of aircraft symmetry, aerodynamic control, force and moment coefficient of aircraft and its static stability and control. T.I. Fossen present an approach to mathematical modelling of aircraft and satellite [2]. J. Blakelock discuss the automatic control of aircraft and comment on its stability [4].

Model predictive control has grown significantly throughout the most recent two decades, both inside the research control group and in the industry. A general disturbance model which suit unmeasured noise entering through the process data, output or state is presented by K.R. Muske and T.A. Badgwell while A. Bemporad, M. Morari and J. Maciejowski presents the explicit state feedback solution to linear quadratic optimal control issue subjected to the state and input constraints [7–9]. E.F. Camacho and C. Bordons focuses on implementation issues for model predictive control and intended to present easy way of implementing them in the industry [10]. A. Suardi and G. constantinides present a system on a chip model predictive control, implemented on a field programmable gate array [6]. M. Kale and A. Chipperfield present formulation of model predictive control scheme implemented to a realistic nonlinear model of an aircraft [24].

Aircraft engines constitutes a complex system, obliging satisfatory observation to guarantee flight safety and timely maintenance. With a specific end goal to observing the aircract engine Y. Guan, J. Warng and T. Lee present a technique of digital simulation for the aircraft turbofan engine control system called method of spare parts [13]. H. Spang and H. Brown review the basics of controlling an engine while satisfying numerous constraints [14]. P. Shankar and M. Siddiqi discuss a nonlinear mathematical model of two shaft turbofan engine utilizing the first principal [15]. A. Alexiou and K. Mathioudakis talk about the demonstrating of a turbine engine utilizing a general purpose simulation tool EcosimPro [21]. On the other hand, F. Correa, A. Oliviera and R. Bosa gives an idea about turbo shaft nonlinear dynamical model and its control system used for electric power generation [22]. C. Kong and J. Park give a overview on a turbine engine for unmanned aerial vehicle [23].

Lately, impressive research endeavors has been given to fault identification of nonlinear systems. For this reason, different methodology have been presents in the literature. W. Xue, Y. Guo and X. Zhang presented Kalman filter techniques for the detection of the fault in sensor and actuators [19]. W. Merrill and W. Bruton also utilized a bank of Kalman filters for identification of sensor faulr and its seclusion of an aircraft engine [25]. M. Seok and B. Jung works on techniques of speed and surge control of an unmanned aircraft vehical with turbojet engine [26]. X. Zhang, L. Tang and J. Decastro present a fault identification and seclusion scheme by using nonlinear adaptation estimator methodolgy for aircraft engines [1]. F. Lu and J. Huang present a model based approach for optimal estimation of engine performances [27]. A Kalman filter was applied by C. Hajiyev and F. Caliskan [28]. This method pertains to the flaws that influences the mean of innovation sequence of the Kalman filter . A sensor flaw could be identified and secluded if it changes the innovation sequence mean value. A Robust Kalman Filter was utilized to recognize the actuator and sensor flaw. But this technique could not utilize to separate which actuator is defective.

1.3 Motivation of the thesis

The issues of reliability, affordability, safety and system integrity have turn out to be progressively imperative as the mishap in the aircraft is increasing because of the system malfunctions. Therefore, it is important to identify the occurrence of faulty conditions in the aircraft and to isolate these faults. By enabling the fault diagnosis strategy for aircraft engine can remarkably enhance the flight safety.

Model predictive control can consider hard constraints on the system. It can easily be tuned and can also be applied to MIMO systems, which is advantage of the model predictive controller over PID, LQ and H_∞ controller.

State estimates can provide valuable information about important variables of the physical process. Controller can use this valuable information about the process to control it more accurately. In other words, System estimators can be a practical or economical alternative to real measurement. The Kalman filter is the most important algorithm for the state estimation.

1.4 Problem Statement of the thesis

The increasing complexity of aerospace system, aircraft and engine maintenance operators are increasingly demanding more intelligence, automation capabilities and functionalities for diagnosis and system malfunctions. Increasing the functionality for fault diagnosis, system and propulsion malfunctions is necessary for flight safety.

1.5 Objective of the thesis

- To design an efficient model of aircraft in Matlab and simulate the designed model in Simulink and to comment the different stability mode of the aircraft model.
- To design an efficient control law to achieve specific performance of the aircraft mode. The specific performance is to achieve the set point of input while keeping the output in a particular limit.
- To design an efficient model of a two shaft engine turbine engine in Simulink
- To design an efficient algorithm for the aircraft engine to detect its faults and to isolate these faults.

1.6 Road Map to the thesis

The road map to the thesis is as follows:

- **Chapter 2:** The study of dynamics (kinematics and kinetics) of an aircraft and an open loop study of aircraft with some proper modeling assumption are being dealt in this chapter.

- **Chapter 3:** A model predictive controller has been proposed for the control of pitch angle, sideslip angle and roll angle of the aircraft, in which continuous time model predictive control strategy is developed.

- **Chapter 4:** Deals with study of dynamics of fan shaft and core shaft of a two shaft gas turbine engine.

- **Chapter 5:** A fault detection and isolation strategy has been present for detection of speed sensor fault in a two spool gas turbine engine. In fault detection and isolation strategy, a bank of Kalman filter is apply for identification and seclusion of faults.

- **Chapter 6:** Conclusion of the thesis along with some future suggestions are presented in this very chapter

Chapter 2

Modeling of the Aircraft System

Chapter 2

Modeling of the Aircraft System

For any type of aircraft the first step in obtaining the accurate mathematical model is to determine stability and control derivatives. These derivatives will impact the flying characteristics and will be used to size control surface, design flight control system and program devise such as simulator. Three approaches can be taken towards completing this goal.

The first and easiest method requires the knowledge of the geometry and inertial properties of the aircraft and employ simple calculation to obtain the derivatives within reasonable accuracy. The second method involves the use of wind tunnels. However, the results will have to be refined after several scale, interference and dynamic effects are taken into account. This method is much more complicated than the previous one, but usually more accurate. The final approach which is the most time consuming and costly but with the most promise and precision in flight testing. Dynamic flight test data is used through techniques such as parameter estimation to accurately estimate the stability and control derivatives. Of course limitation in availability of data and noisy measurements can cause serious problems in the successful resolution of all the derivatives of interest.

In the design of the mathematical model of the aircraft in Matlab / Simulink, we consider only the first method which uses the knowledge of the geometry and inertial properties of the aircraft. Using the laws of kinetic and kinematic the equation of motion of the aircraft is derived and linearized about longitudinal equilibrium.

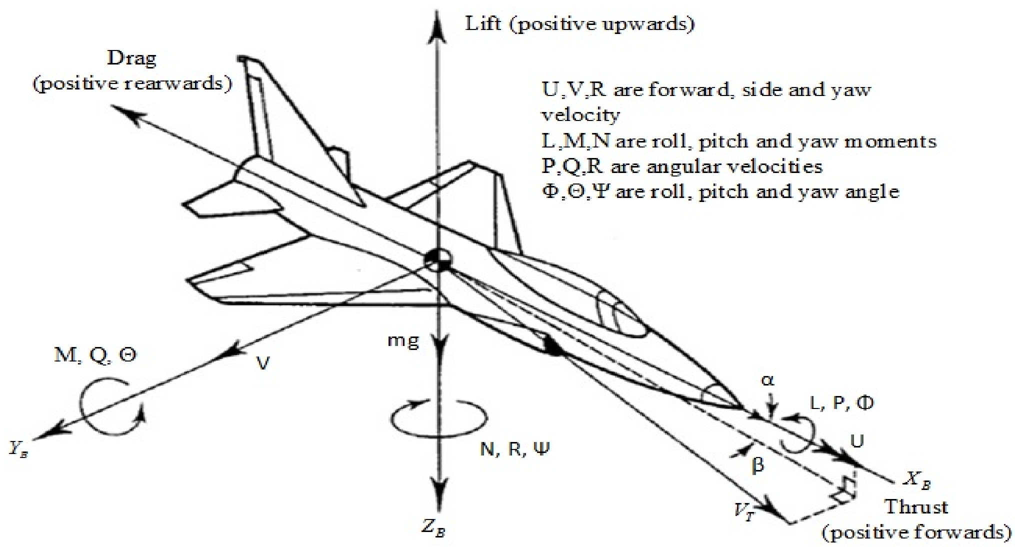

Figure 2.1: Direction of Body axis, Euler angles, Moments, Forces and Velocities related to the Aircraft System

The aircraft model can easily be understood by understanding the equations that govern the motion of the aircraft. These equations governing the motion of aircraft can be derived from the basic laws of kinetic and kinematic. The equations governing the aircraft motion are linearized (since nonlinear) utilizing the theory of perturbation and finally gives the state space models for longitudinal motion and lateral motion.

2.1 Aircraft State Space Vectors

To derive the equations of motion, first we define aircraft state space vectors as

2.1.1 Vector of Aircraft Velocity

$$\nu = \begin{bmatrix} U \\ V \\ W \\ P \\ Q \\ R \end{bmatrix} = \begin{bmatrix} velocity\ in\ forward\ direction \\ velocity\ in\ transverse\ direction \\ velocity\ in\ verticle\ direction \\ rate\ of\ roll\ motion \\ rate\ of\ pitch\ motion \\ rate\ of\ yaw\ motion \end{bmatrix}$$

where, $V_T = \sqrt{U^2 + V^2 + W^2}$ is the velocity of the aircraft.

2.1.2 Vector of Aircraft Position

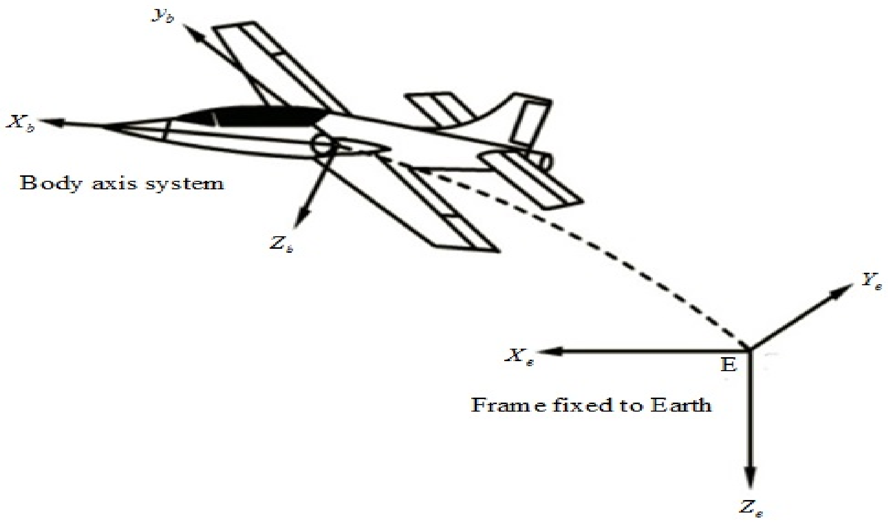

Figure 2.2: Earth fixed and Body fixed Co-ordinate System

$$\eta = \begin{bmatrix} X_e \\ Y_e \\ Z_e, h \\ \Phi \\ \Theta \\ \Psi \end{bmatrix} = \begin{bmatrix} earth\ fixed\ x - axis \\ earth\ fixed\ y - axis \\ earth\ fixed\ z - axis \\ angle\ of\ roll \\ angle\ of\ pitch \\ angle\ of\ yaw \end{bmatrix}$$

2.1.3 Vector of Forces and Moments

$$\tau = \begin{bmatrix} X \\ Y \\ Z \\ L \\ M \\ N \end{bmatrix} = \begin{bmatrix} force\ in\ longitudinal\ direction \\ force\ in\ transverse\ direction \\ force\ in\ verticle\ direction \\ moment\ in\ rolling \\ moment\ in\ pitching \\ moment\ in\ yawing \end{bmatrix}$$

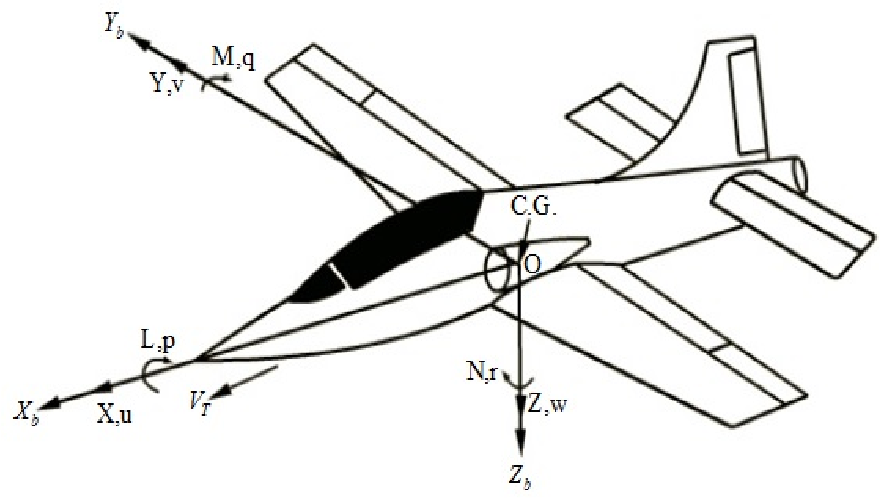

Figure 2.3: The moments and forces acting on an aircraft and component of angular and linear velocities with reference to body axis system

2.1.4 Vector of Actuator Control Input to Aircraft

$$\epsilon = \begin{bmatrix} \delta_T \\ \delta_A \\ \delta_E \\ \delta_F \\ \delta_R \end{bmatrix} = \begin{bmatrix} thrust \\ aileron \\ elevator \\ flap \\ rudder \end{bmatrix}$$

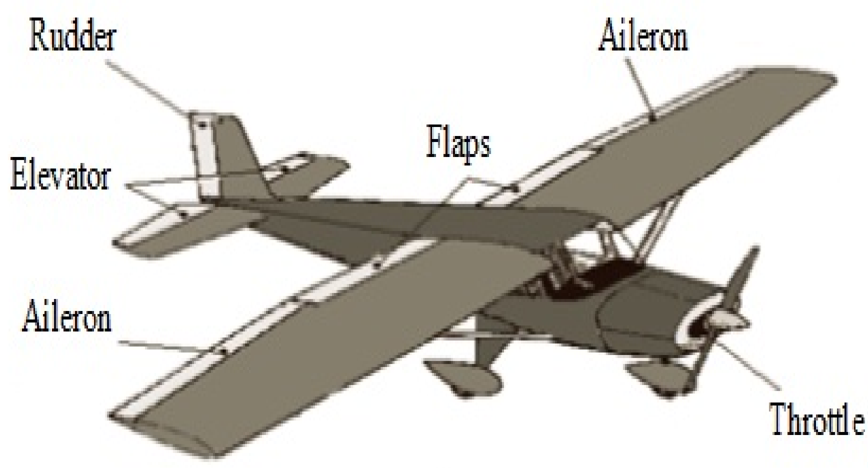

Figure 2.4: Actuator inputs of an aircraft

2.2 Rotation Matrix

The total velocity of the aircraft (V_T) is in the direction of the wind axis. To find the relation between aircraft body axis and wind axis we rotate the body axis system about z-axis by a negative unit of sideslip angle (β) than new coordinate system is now rotated about new y-axis by a positive unit of angle of attack (α)

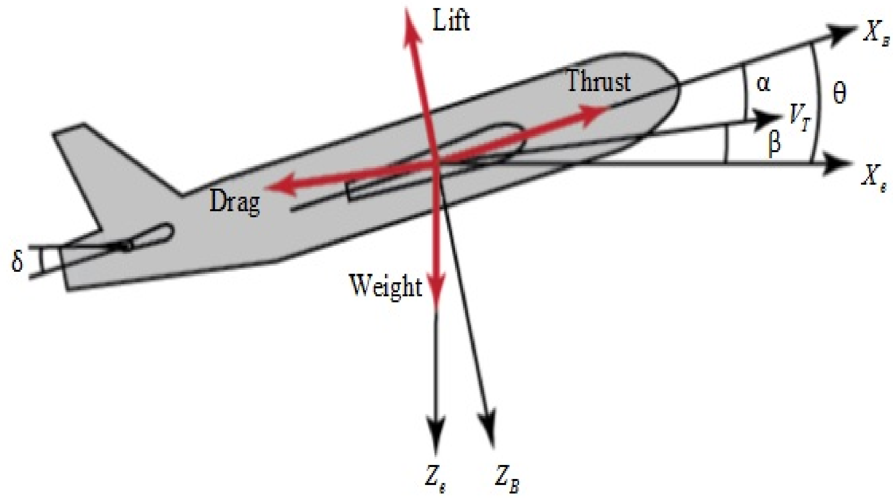

Figure 2.5: Definition of Rotation angles for an angle

$$R_{Body}^{Wind} = \begin{bmatrix} \cos\beta\cos\alpha & \sin\beta & \cos\beta\sin\alpha \\ -\sin\beta\cos\alpha & \cos\beta & -\sin\beta\sin\alpha \\ -\sin\alpha & 0 & \cos\alpha \end{bmatrix}$$

Therefore, velocity of the aircraft in body axis system is-

$$V^{Body} = R_{Body}^{Wind^T} V^{Wind}$$

$$\begin{bmatrix} U \\ V \\ W \end{bmatrix} = \begin{bmatrix} V_T\cos\beta\cos\alpha \\ V_T\sin\beta \\ V_T\sin\beta\sin\alpha \end{bmatrix} \tag{2.1}$$

If the values of α and β are small enough such that $\cos\alpha = 1$ and $\sin\beta = \beta$ Then, from equation (2.1),

$$\begin{aligned} U &= V_T \\ \beta &= \frac{V}{V_T} \\ \alpha &= \frac{W}{V_T} \end{aligned} \tag{2.2}$$

2.3 Equations of Motion for the Aircraft

2.3.1 Kinematic Equations

Kinematic equation of translational motion for body axis ($X_B\ Y_B\ Z_B$) with respect to local axis ($X_e\ Y_e\ Z_e$) can be obtain by rotating the body axis by Euler angles $\Theta,\ \Phi,\ and\ \Psi$.

$$\begin{bmatrix} \dot{X}_e \\ \dot{Y}_e \\ \dot{Z}_e \end{bmatrix} = \begin{bmatrix} \cos\Theta\cos\Psi & \cos\Psi\sin\Theta\sin\Psi - \sin\Psi\cos\Phi & \cos\Psi\cos\Phi\sin\Theta + \sin\Psi\sin\Phi \\ \cos\Theta\sin\Psi & \sin\Phi\sin\Theta\sin\Psi + \cos\Psi\cos\Phi & \sin\Theta\sin\Psi\cos\Phi - \cos\Psi\sin\Phi \\ -\sin\Theta & \sin\Psi\cos\Theta & \cos\Phi\cos\Theta \end{bmatrix} \tag{2.3}$$

Kinematic equations of rotational motion are

$$\begin{bmatrix} \dot{\Phi} \\ \dot{\Theta} \\ \dot{\Psi} \end{bmatrix} = \begin{bmatrix} 1 & \tan\Theta\sin\Phi & \tan\Theta\cos\Phi \\ 0 & \cos\Phi & -\sin\Phi \\ 0 & \frac{\sin\Phi}{\cos\Theta} & \frac{\cos\Phi}{\cos\Theta} \end{bmatrix} \begin{bmatrix} P \\ Q \\ R \end{bmatrix} \tag{2.4}$$

where, $\cos\Theta \neq 0$

2.3.2 Kinetic Equations

Newton's second law is utilized to derive the rigid body dynamic equations and It's analogous for angular motion as-

$$m(\dot{\nu}_1 + \nu_1\nu_2) = \tau_1 \tag{2.5}$$

$$I_{CG}\dot{\nu}_2 + \nu_2(I_{CG}\nu_2) = \tau_2 \tag{2.6}$$

where,

$$\nu_1 = \begin{bmatrix} U \\ V \\ W \end{bmatrix} \qquad \nu_2 = \begin{bmatrix} P \\ Q \\ R \end{bmatrix} \qquad \tau_1 = \begin{bmatrix} X \\ Y \\ Z \end{bmatrix} \qquad \tau_2 = \begin{bmatrix} L \\ M \\ N \end{bmatrix}$$

Remark- It is assume that the coordinate system is located in the center of gravity point of the aircraft therefore, for symmetric plane $I_{xy} = I_{yz} = 0$.
Hence resulting model can be written as-

$$M_{RB}\dot{\nu} + C_{RB}(\nu)\nu = \tau_{RB} \tag{2.7}$$

The affect of moments and forces on the aircraft come from the aerodynamics, control forces and gravitational forces. The most important force in the flight is gravity which act at the center of gravity point of the aircraft and parallel to local Z-axis. Therefore, effect of the gravitational force on the aircraft is given as-

$$f_G = \begin{bmatrix} 0 \\ 0 \\ mg \end{bmatrix}$$

In earth fixed $(X_e \; Y_e \; Z_e)$ coordinate system

$$g(\eta) = -R_{X_b \; Y_b \; Z_b}^{X_e \; Y_e \; Z_e \; T} f_G$$

$$g(\eta) = \begin{bmatrix} mg\sin\Theta \\ -mg\sin\Phi\cos\Theta \\ -mg\cos\Phi\cos\theta \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

If a generalized vector τ includes aerodynamics and control forces, then the moments and forces affecting the aircraft are-

$$\tau_{RB} = -g(\eta) + \tau \tag{2.8}$$

Therefore, the kinetic equations of the aircraft can be written as $from\ equation$ (2.6) and(2.7)

$$M_{RB}\dot{\nu} + C_{RB}(\nu)\nu + g(\eta) = \tau \tag{2.9}$$

In component form

$$\begin{aligned}
m(\dot{U} - RV + QW + g\sin\Theta) &= X \\
m(\dot{V} - WP + UR - g\cos\Theta\sin\Phi) &= Y \\
m(\dot{W} - QU + VP - g\cos\Theta\cos\Phi) &= Z \\
I_X\dot{P} - I_{XZ}(\dot{R} + PQ) + (I_Z - I_Y)QR &= L \\
I_y\dot{Q} - I_{XZ}(P^2 - R^2) + (I_X - I_y)PR &= M \\
I_Z\dot{R} - I_{XZ}\dot{P} - (I_X - I_Y)PQ + I_{XZ}RQ &= N
\end{aligned} \tag{2.10}$$

2.4 Linearization of Equations

According to Linear theory that the state can be written as sum of a nominal value (generally constant) and a perturbation (derived from nominal value). The equation (2.9) develop previously are nonlinear and coupled. These equations can be simplify easily when the equilibrium condition is chosen corresponding to the longitudinal equilibrium, in which the velocity and gravity vector are in the plane of symmetry of vehicle.

Therefore,

$$U = u_0 + u \qquad P = p \tag{2.11}$$

$$V = v \qquad Q = q \tag{2.12}$$

$$W = w \qquad R = r \tag{2.13}$$

$$\Theta = \theta_0 + \theta \qquad \Phi = \phi \tag{2.14}$$

The trim values of all lateral directional variables are zero because the initial trim condition corresponds to the longitudinal equilibrium ($v_0 = p_0 = r_0 = \phi_0$). The value W_0 is zero because we are using stability axis and the value q_0 is zero because we are restricting the equilibrium state to have no normal acceleration.

2.4.1 Equilibrium States

Equilibrium state can be written as-

$$\begin{aligned} mg_0 \sin\theta_0 &= X_0 \\ -mg_0 \cos\theta_0 &= Z_0 \\ M_0 = L_0 = Y_0 &= N_0 = 0 \end{aligned} \tag{2.15}$$

2.4.2 Perturbed Equations

The perturbed equations can be obtained using equations (2.11), (2.12) and (2.10). Neglect the higher order terms of the perturbed states. After perturbation the moments and forces equations can be written as-

$$m(\dot{u} + g_0 \cos\theta_0 \theta) = \delta X$$

$$m(\dot{w} - u_0 q + g_0 \sin\theta_0 \theta) = \delta Z$$

$$m(\dot{v} + u_0 r - g_0 \cos\theta_0 \phi) = \delta Y$$

$$I_X \dot{p} - I_{XZ} \dot{r} = \delta L$$

$$I_Y\dot{q} = \delta M \tag{2.16}$$

$$I_z\dot{r} - I_{XZ}\dot{p} = \delta N$$

$$\dot{\theta} = q$$

$$\begin{bmatrix} \dot{\phi} \\ \dot{\psi} \end{bmatrix} = \begin{bmatrix} 1 & \tan\theta_0 \\ 0 & \frac{1}{\cos\theta_0} \end{bmatrix} \begin{bmatrix} p \\ r \end{bmatrix} ;\ \cos\theta_0 \neq 0$$

2.5 Aerodynamic Moments and Forces

The perturbation in aerodynamic moments and forces are function of both state variable and control inputs, which can be written as-

2.5.1 Longitudinal Mode

$$\begin{bmatrix} \delta X \\ \delta Z \\ \delta M \end{bmatrix} = \begin{bmatrix} X_{\dot{u}} & X_{\dot{\alpha}} & X_{\dot{q}} \\ Z_{\dot{u}} & Z_{\dot{\alpha}} & Z_{\dot{q}} \\ M_{\dot{u}} & M_{\dot{\alpha}} & M_{\dot{q}} \end{bmatrix} \begin{bmatrix} \dot{u} \\ \dot{\alpha} \\ \dot{q} \end{bmatrix} + \begin{bmatrix} X_u & X_\alpha & X_q \\ Z_u & Z_\alpha & Z_q \\ M_u & M_\alpha & M_q \end{bmatrix} \begin{bmatrix} u \\ \alpha \\ q \end{bmatrix} + \begin{bmatrix} X_{\delta e} & X_{\delta T} \\ Z_{\delta e} & Z_{\delta T} \\ M_{\delta e} & M_{\delta T} \end{bmatrix} \begin{bmatrix} \delta_e \\ \delta_T \end{bmatrix}$$

For the conventional aircraft the following aerodynamics coefficient can be neglected, i.e. $X_{\dot{u}}$ $X_{\dot{\alpha}}$ $X_{\dot{q}}$ $Z_{\dot{u}}$ $Z_{\dot{q}}$ $X_{\dot{u}}$ $X_{\dot{\alpha}}$ $X_{\dot{q}}$ are neglected. Hence, equation for longitudinal mode of aerodynamic forces and moments reduces to

$$\begin{bmatrix} \delta X \\ \delta Z \\ \delta M \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & Z_{\dot{\alpha}} & 0 \\ 0 & M_{\dot{\alpha}} & 0 \end{bmatrix} \begin{bmatrix} \dot{u} \\ \dot{\alpha} \\ \dot{q} \end{bmatrix} + \begin{bmatrix} X_u & X_\alpha & 0 \\ Z_u & Z_\alpha & Z_q \\ M_u & M_\alpha & M_q \end{bmatrix} \begin{bmatrix} u \\ \alpha \\ q \end{bmatrix} + \begin{bmatrix} X_{\delta e} & X_{\delta T} \\ Z_{\delta e} & Z_{\delta T} \\ M_{\delta e} & M_{\delta T} \end{bmatrix} \begin{bmatrix} \delta_e \\ \delta_T \end{bmatrix} \tag{2.17}$$

2.5.2 Lateral Mode

$$\begin{bmatrix} \delta Y \\ \delta L \\ \delta N \end{bmatrix} = \begin{bmatrix} Y_{\dot{\beta}} & Y_{\dot{p}} & Y_{\dot{r}} \\ L_{\dot{\beta}} & L_{\dot{p}} & L_{\dot{r}} \\ N_{\dot{\beta}} & N_{\dot{p}} & N_{\dot{r}} \end{bmatrix} \begin{bmatrix} \dot{\beta} \\ \dot{p} \\ \dot{r} \end{bmatrix} + \begin{bmatrix} Y_\beta & Y_p & Y_r \\ L_\beta & L_p & L_r \\ N_\beta & N_p & N_r \end{bmatrix} \begin{bmatrix} \beta \\ p \\ r \end{bmatrix} + \begin{bmatrix} Y_{\delta a} & Y_{\delta r} \\ M_{\delta a} & M_{\delta r} \\ N_{\delta a} & N_{\delta r} \end{bmatrix} \begin{bmatrix} \delta_a \\ \delta_r \end{bmatrix}$$

For the conventional aircraft the following aerodynamics coefficient can be neglected, i.e. $Y_{\dot{\beta}}$ $Y_{\dot{p}}$ $Y_{\dot{r}}$ $L_{\dot{\beta}}$ $L_{\dot{p}}$ $L_{\dot{r}}$ $N_{\dot{\beta}}$ $N_{\dot{p}}$ $N_{\dot{r}}$ $Y_{\delta a}$ are neglected. Hence, equation for longitudinal mode of aerodynamic forces and moments reduces to

$$\begin{bmatrix} \delta Y \\ \delta L \\ \delta N \end{bmatrix} = \begin{bmatrix} Y_\beta & Y_p & Y_r \\ L_\beta & L_p & L_r \\ N_\beta & N_p & N_r \end{bmatrix} \begin{bmatrix} \beta \\ p \\ r \end{bmatrix} + \begin{bmatrix} 0 & Y_{\delta r} \\ M_{\delta a} & M_{\delta r} \\ N_{\delta a} & N_{\delta r} \end{bmatrix} \begin{bmatrix} \delta_a \\ \delta_r \end{bmatrix} \tag{2.18}$$

2.6 Decoupled State Space Model

A state space model for decoupled longitudinal mode as well as lateral mode can be write by combining equations (2.2, 2.16, 2.17, 2.18).

2.6.1 State Space Model for Longitudinal Mode

From equations (2.2, 2.16, 2.17), we can write the equations governing the motion of aircraft in longitudinal mode as-

$$\begin{aligned} \dot{u} &= X_u u + X_\alpha \alpha + g_0 \cos\theta_0 \theta + X_{\delta e}\delta_e + X_{\delta T}\delta_T \\ (1 - Z_{\dot{\alpha}})\dot{\alpha} &= Z_u u + Z_\alpha \alpha + (Z_q + u_0)q - g_0 \sin\theta_0 \theta + Z_{\delta e}\delta_e + Z_{\delta T}\delta_T \\ \dot{q} &= M_u u + M_{\dot{\alpha}}\dot{\alpha} + M_\alpha \alpha + M_q q + M_{\delta e}\delta_e + M_{\delta T}\delta_T \\ \dot{\theta} &= q \end{aligned} \tag{2.19}$$

If we introduce longitudinal state vector $X = [u \ w \ q \ \theta]'$ and control vector $\epsilon = [\delta_e \ \delta_T]'$ Then equation (2.19) is equivalent to first order state space model

$$I_n \dot{X} = A_n X + B_n \epsilon$$

where,

$$A_n = \begin{bmatrix} X_u & X_\alpha & 0 & g_0\cos\theta_0 \\ Z_u & Z_\alpha & (Z_q+u_0) & g_0\sin\theta_0 \\ M_u & M_\alpha & M_q & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \qquad B_n = \begin{bmatrix} X_{\delta e} & X_{\delta T} \\ Z_{\delta e} & Z_{\delta T} \\ M_{\delta e} & M_{\delta T} \\ 0 & 0 \end{bmatrix}$$

$$I_n = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1-Z_{\dot\alpha} & 0 & 0 \\ 0 & -M_{\dot\alpha} & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \qquad I_n^{-1} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & \frac{1}{1-Z_{\dot\alpha}} & 0 & 0 \\ 0 & \frac{M_{\dot\alpha}}{1-Z_{\dot\alpha}} & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

Since aircraft mass factor (μ) is usually large (approximately 100), Therefore it is usual to neglect $Z_{\dot\alpha}$ with respect to unity and Z_q with respect to u_0. By premultiplying I_n^{-1}, the state space model of longitudinal mode takes the standard form as

$$\dot X = AX + B\epsilon \tag{2.20}$$

where,

$$A = \begin{bmatrix} X_u & X_\alpha & 0 & -g_0\cos\theta_0 \\ Z_u & Z_\alpha & u_0 & -g_0\sin\theta_0 \\ M_u + M_{\dot\alpha}Z_u & M_\alpha + M_{\dot\alpha}Z_\alpha & M_q + M_{\dot\alpha}u_0 & -M_{\dot\alpha}g_0\sin\theta_0 \\ 0 & 0 & 1 & 0 \end{bmatrix}$$

$$B = \begin{bmatrix} X_{\delta e} & X_{\delta T} \\ Z_{\delta e} & Z_{\delta T} \\ M_{\delta e} + M_{\dot\alpha}Z_{\delta e} & M_{\delta T} + M_{\dot\alpha}Z_{\delta T} \\ 0 & 0 \end{bmatrix}$$

2.6.2 State Space Model for Lateral Mode

From equations (2.2, 2.16, 2.18), we can write the lateral mode of equations of motion as -

$$\dot\beta = Y_\beta\beta + Y_p p + (Y_r + u_0)r - g_0\cos\theta_0\phi + Y_{\delta a}\delta_a + Y_{\delta r}\delta_r$$

$$\dot{p} = L_p p + L_\beta \beta + L_r r + \frac{I_{XZ}}{I_X}\dot{r} + L_{\delta r}\delta_r + L_{\delta a}\delta_a$$
$$\dot{r} = N_p p + N_\beta \beta + N_r r + \frac{I_{XZ}}{I_X}\dot{p} + N_{\delta r}\delta_r + N_{\delta a}\delta_a \tag{2.21}$$
$$\begin{bmatrix} \dot{\phi} \\ \dot{\psi} \end{bmatrix} = \begin{bmatrix} 1 & \tan\theta_0 \\ 0 & \frac{1}{\cos\theta_0} \end{bmatrix} \begin{bmatrix} p \\ r \end{bmatrix} ;\ \cos\theta_0 \neq 0$$

If we introduce lateral state vector $X = [\beta\ p\ \phi\ r]'$ and control vector $\epsilon = [\delta_a\ \delta_r]'$ Then equation (2.21) is equivalent to first order state space model

$$I_n \dot{X} = A_n X + B_n \epsilon$$

where,

$$A_n = \begin{bmatrix} Y_\beta & Y_p & g_0\cos\theta_0 & Y_r - u_0 \\ L_\beta & L_p & 0 & L_r \\ 0 & 1 & 0 & 0 \\ N_\beta & N_p & 0 & N_r \end{bmatrix} \qquad B_n = \begin{bmatrix} 0 & Y_{\delta r} \\ L_{\delta a} & L_{\delta r} \\ 0 & 0 \\ N_{\delta a} & N_{\delta r} \end{bmatrix}$$
$$I_n = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & -\frac{I_{XZ}}{I_X} \\ 0 & 0 & 1 & 0 \\ 0 & -\frac{I_{XZ}}{I_Z} & 0 & 1 \end{bmatrix}$$

For most of the aircraft, the ratio $\frac{I_{XZ}}{I_X}$ *and* $\frac{I_{XZ}}{I_Z}$ are quite small so we can neglect these ratio with respect to unity. Therefore, the state space model of the lateral mode takes the standard form as

$$\dot{X} = AX + B\epsilon \tag{2.22}$$

where,

$$A = \begin{bmatrix} Y_\beta & Y_p & g_0\cos\theta_0 & Y_r - u_0 \\ L_\beta & L_p & 0 & L_r \\ 0 & 1 & 0 & 0 \\ N_\beta & N_p & 0 & N_r \end{bmatrix} \qquad B = \begin{bmatrix} 0 & Y_{\delta r} \\ L_{\delta a} & L_{\delta r} \\ 0 & 0 \\ N_{\delta a} & N_{\delta r} \end{bmatrix}$$

2.7 State Space Model for the Aircraft B-767

2.7.1 Longitude Mode

Given, equilibrium point:

$$Velocity\ V_T = 890\ ft/s \qquad Altitude\ h = 35000\ ft$$

$$Mass\ m = 184000\ lbs \qquad Mach\ No.\ M = 0.8$$

If $X = [u\ w\ q\ \theta]'$ and $\epsilon = [\delta_e\ \delta_T]'$ are longitudinal state and control vector respectively then, state equation is-

$$\dot{X} = AX + B\epsilon$$

where,

$$A = \begin{bmatrix} -0.0168 & 0.1121 & 0.0003 & -0.5608 \\ -0.0164 & -0.7771 & 0.9945 & 0.0015 \\ -0.0417 & -3.6595 & -0.9544 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}; \ B = \begin{bmatrix} -0.0243 & 0.0519 \\ -0.0634 & -0.0005 \\ -3.6942 & 0.0243 \\ 0 & 0 \end{bmatrix}$$

The state space model of the aircraft B-767 for longitudinal mode in Simulink is

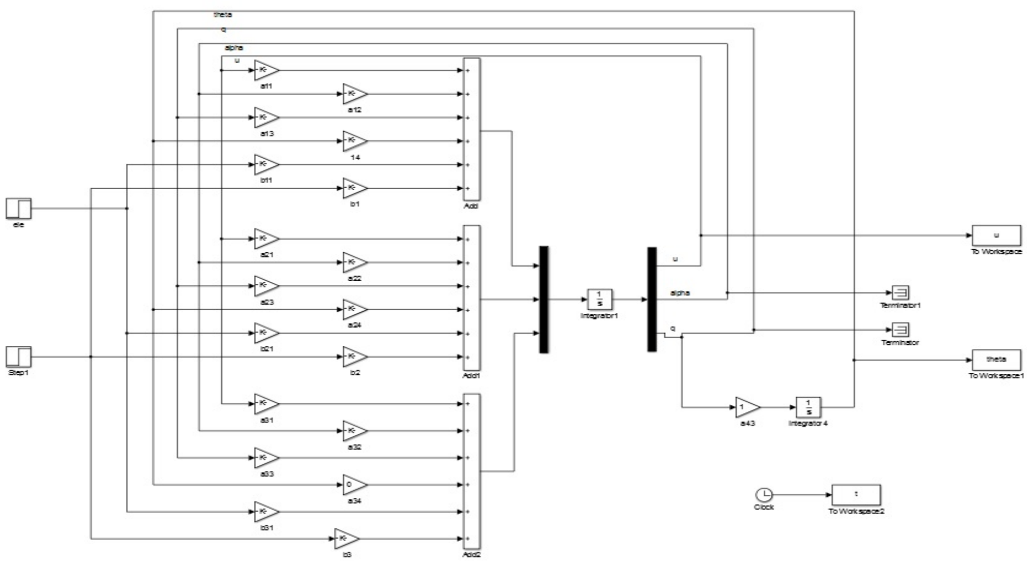

Figure 2.6: Simulink Model of Longitudinal Mode of Aircraft B-767 System

The Eigen value of the states matrix are

Eigen Value	Damping	Frequency(rad/sec)
$-8.88e^{-1} + \iota 1.91$	$4.22e^{-1}$	$2.1e^{0}$
$-8.88e^{-1} - \iota 1.91$	$4.22e^{-1}$	$2.1e^{0}$
$-6.39e^{-3} + \iota 5.9e^{-2}$	$1.08e^{-1}$	$5.94e^{-2}$
$-6.39e^{-3} - \iota 5.9e^{-2}$	$1.08e^{-1}$	$5.94e^{-2}$

These Eigen value shows that the aircraft longitudinal dynamics has two different modes one at lower frequency $5.94e^{-2}$ rad/s andother at relaitvely higher frequency 2.10 rad/s. Low frequency mode is lightly damped ($damping\ ratio =$ 0.108) called as Phugoid mode. High frequency mode is relatively heavily damped ($damping\ ratio = 0.422$) called as Short Period SP mode.

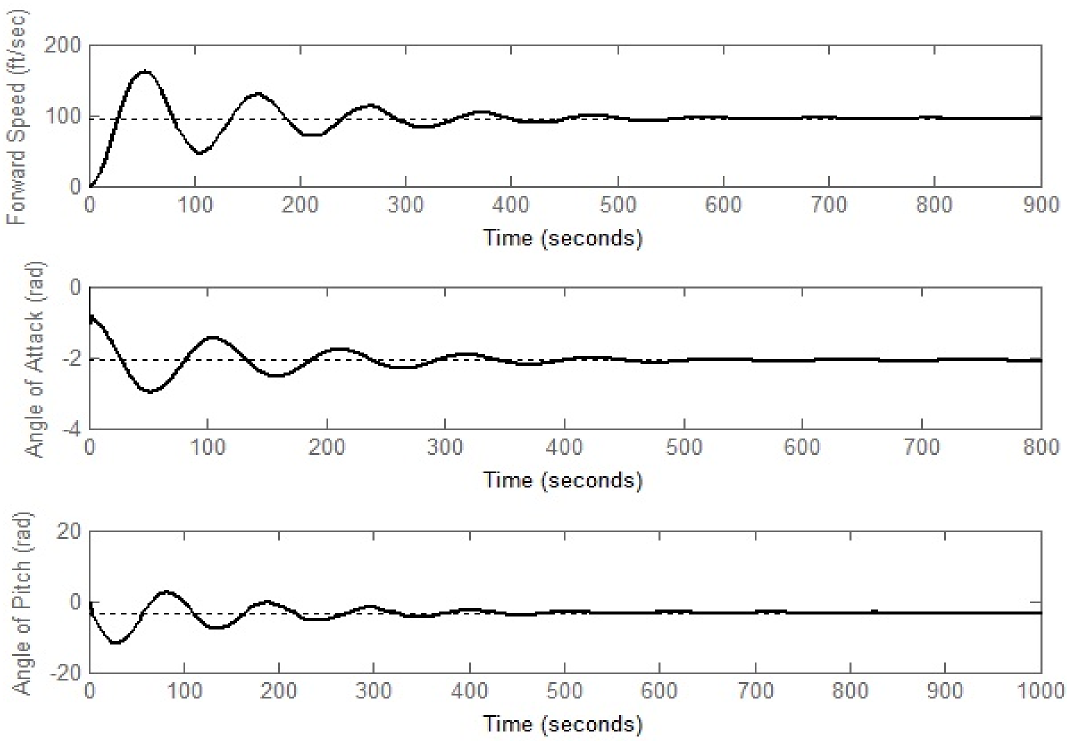

Figure 2.7: Step response of the Longitudinal Mode of Aircraft B-767

In SP mode, motion is rapid pitching of of aircraft about its the center of gravity. SP pitching oscillation is most visible in initial instant of the variable pitch rate and angle of attack. SP mode is so short that the speed and pitch angle do not have time to damp, that is why the oscillations are the variations in angle of attack.

Phugoid mode describes the long duration translatory motion of center of gravity point of the vehicle. Phugoid mode can be excited by an elevator singlet resulting in a pitch increase with no change in trim condition from the cruise condition. In Phugoid mode, the angle of attack remain nearly constant but varying the pitch caused by a repeated exchange of airspeed and altitude.

2.7.2 Lateral Mode

Given, equilibrium point:

$$Velocity\ V_T = 890\ ft/s \qquad Altitude\ h = 35000\ ft$$

$$Mass\ m = 184000\ lbs \qquad Mach\ No.\ M = 0.8$$

If $X = [v\ p\ \phi\ r]'$ and $\epsilon = [\delta_a\ \delta_r]'$ are lateral state and control vector respectively then, state equation is-

$$\dot{X} = AX + B\epsilon$$

where,

$$A = \begin{bmatrix} -0.1245 & 0.0350 & 0.0414 & -0.9962 \\ -15.2138 & -2.0587 & 0.0032 & 0.6458 \\ 0 & 1 & 0 & 0.0357 \\ 1.6447 & -0.0447 & -0.0022 & -0.1416 \end{bmatrix};\ B = \begin{bmatrix} -0.0049 & 0.0237 \\ -4.0379 & 0.9613 \\ 0 & 0 \\ -0.0568 & -1.2168 \end{bmatrix}$$

The state space model of the aircraft B-767 for lateral mode in Simulink is

The Eigen value of the states matrix are

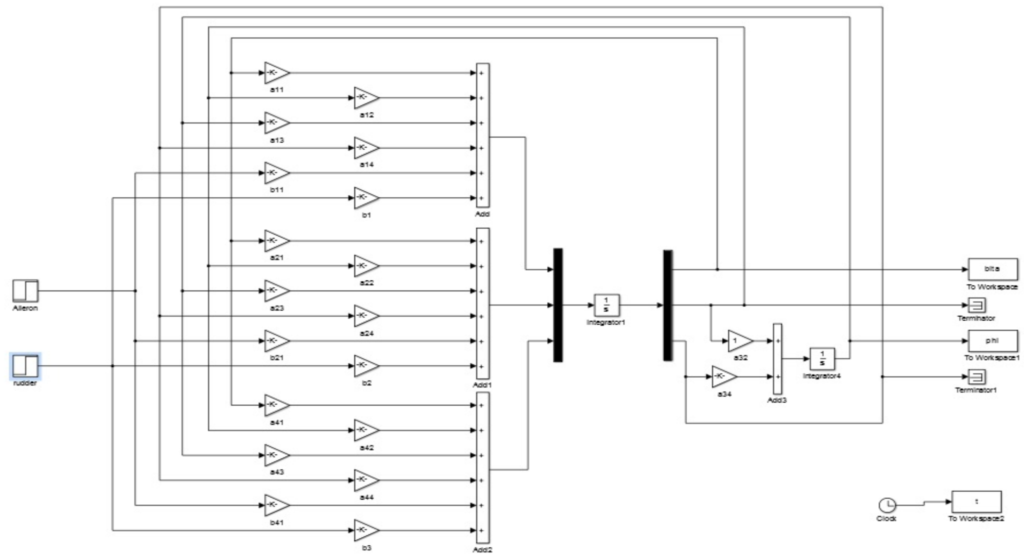

Figure 2.8: Simulink Model of Lateral Mode of Aircraft B-767 System

Eigen Value	Damping	Frequency(rad/sec)
$-2.09e^{0}$	$1.0e^{0}$	$2.9e^{0}$
$-1.12e^{-1} + \iota 1.5$	$7.45e^{-2}$	$1.5e^{0}$
$-1.12e^{-1} - \iota 1.5$	$7.45e^{-2}$	$1.5e^{0}$
$-1.43e^{-2}$	$1.0e^{0}$	$1.43e^{-2}$

These Eigen values show that the lateral dynamics has three distinct mode, one is damped oscillatory and two exponential mode. The oscillatory mode is lightly damped ($damping\ ratio = 0.745$) and for short duration at frequency ($1.5\ rad/s$), called as Dutch Roll (DR) mode. One of the exponential mode is relatively heavily damped ($damping\ ratio = 1$) at frequency of ($0.0143\ rad/s$), shows the damping of rolling motion of the aircraft, called as Roll mode. The other exponential mode converges very slow as large time constant. It is often unstable (stable in this case), called as Spiral mode.

The Dutch roll mode is lightly damped, short oscillation in yaw coupled with roll. Dutch roll mode can be excited by aileron or rudder singlet. Oscillations is visible in intial instant of sideslip angle and roll rate. Dutch roll mode is the lateral motion equivalent of the short period mode of longitudinal motion.

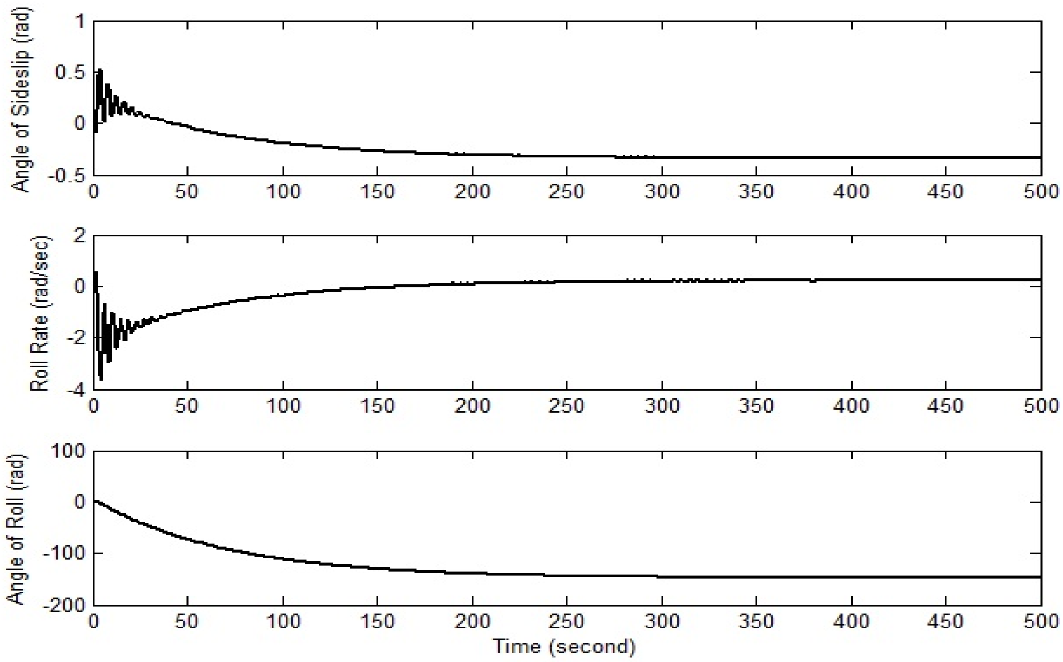

Figure 2.9: Step response of the Lateral Mode of Aircraft B-767

The Roll mode and Spiral mode are non-oscillatory mode. Roll mode consist of purely rolling motion. It converges very quickly with heavily damping. Spiral mode is complex coupled motion in roll, yaw and sideslip. It converges slow as having large time constant. Spiral mode can be excited by a disturbance in sideslip which follows in roll.

Chapter 3

Model Predictive Control Strategy for the Aircraft System

Chapter 3

Model Predictive Control Strategy for the Aircraft System

Model predictive control strategy is controller scheme based on models, which can easily handle basic changes,for example actuator and sensor failure and system parameter changes by adjusting the control strategy on a specimen by test premise. It designated an efficient control methods range, which utilize process model explicitly to obtain the control sequence by optimizing an objective function.

The model predictive control strategy empowers a controller to be produced which is ideal as for a specified quadratic execution record. In numerous pragmatic control issues, it is direct to interpret the obliged performance objective useful into an issue of optimizing a quadratic functional while applying the system constraints on it.

The concept behind choosing the model predictive control is that, the model predictive control has unmistakable point of interest over other kind of control procedures for example, PID, Linear Quadratic and H_∞. A PID controller is effectively tuned however can just be connected to lower order SISO frameworks. Direct Quadratic and H_∞ controller can undoubtedly be connected to MIMO frameworks however can't deal with sign limitations in an sufficient way. Model predictive control can consider hard requirements on the systems.

3.1 Advantage of Model Predictive Control

Model predictive control has many advantages over the other controller some of them are as follows

- It is utilized to control a great variety of procedures, from those with moderately basic dynamics to more complex one, including systems with long delay time or unstable or non-minimum phase one.
- The multivariable case can undoubtedly be managed.
- It presents feed forward control in a natural manner to compensate for measurable unsettling influence.
- Its augmentation to the treatment of imperatives, is adroitly basic and can be methodicallly included amid the outline process.
- It is a completely open approach in view of certain essential standards which takes into account future augmentations.

3.2 Model Predictive Control Strategy

Model predictive control is is a way to deal with controller outline that includes online enhancement count. The improvement issue makes note of framework flow, imperatives and control objective. The customary model predictive control requires the arrangement of an open circle ideal control issue, in which choice variable is an arrangement of control activities at every example time. Current control activity is situated equivalent to the first term of the ideal control arrangement. A key feature to model predictive control is the receding horizon principle, in which current state is optimized by considering the future state into account.

The future outputs $y(k+i|k)$ is predicted for a specific horizon. These predicted output depends on the past input and outputs and future control signal $u(k+i|k)$.

The arrangement of future control sequence is ascertained by minimizing a specific measure to keep the procedure yield near to the reference direction $r(k+i|k)$. This criterion takes the type of quadratic function of the slip between predictive yield signal $y(k+i|k)$ and reference information signal $r(k+i|k)$.

The optimal control signal $u^*(k|k)$ is calculated by optimizing the given criterion and the first element of this control signal is sent to the process while other are rejected. The whole process is repeated with this new value of control signal and all the sequences are brought up to date.

The model predictive control strategy discussed above is a discrete time model predictive control strategy. In designing the model predictive controller for the aircraft model we are using the continuous time model predictive strategy.

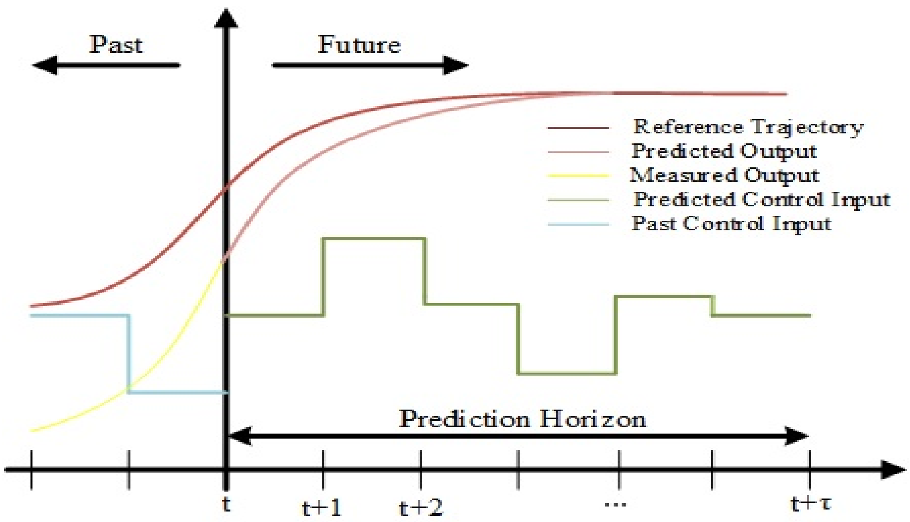

Figure 3.1: Reciding Horizon Principle

At time t the predicted plant output is calculated. This is done for the prediction horizon T_P. Based on the plant predicted output at time $t+T_P$, control action is computed to reduce the system error and follow the reference trajectory. The first step of the calculated control action is executed and updated plant output is measure. This process is repeated continuously. Thus, the system error is eliminated and output follows the input.

To take after the set point, the control sign need to join to a nonzero consistent, i.e. identified with relentless state addition of the plant and extent of the set point change. That is the reason, here, we are utilizing the first derivative of the control sequence as opposed to utilizing it specifically.

3.3 Continuous Time Model Predictive Control Strategy

In the recent years the interest in continuous - time MPC has grown. In the work of Wang [13] it is shown that how to create continuous - time model predictive controller using the orthonormal basic functions. The big advantage of this method is that it reduces the required computing power. In general, CTMPC is more complicated than its discrete time counterpart. This is because in the continuous time case, convolution is utilized to calculate the future plant behavior instead of iteration.

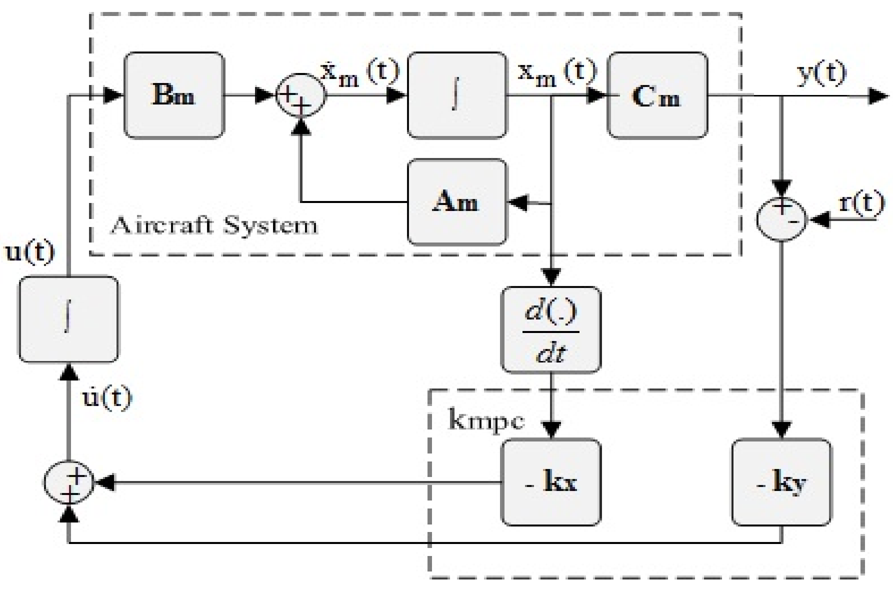

Figure 3.2: Block diagram of Continuous Time Model Predictive Control

The design strategy presented here can be used as an substitute to classical receding horizon control without the need to solve the matrix differential Ricatti equation. The control trajectory is calculated using a pre-chosen set of orthonormal basis functions. The first derivative of the control sequence can be approximated within the prediction horizon using the orthonormal basis function [13]. Laguerre orthonormal basis function is used in this design. The novelty of this approach lies in the way that the issue of finding the optimal control sequence is changed over into one of the finding arrangement of coefficient for the Laguerre model.

3.4 Leguerre Function

One set of Orthonormal basis function frequently used is Laguerre Function. It satisfies the orthonormal property and defined as

$$l_j(t) = \sqrt{2q}\frac{e^{qt}}{j-1!}\frac{d^{j-1}}{dt^{j-1}}[t^{j-1}e^{-2qt}] \tag{3.1}$$

where, $l_j(t)$ is the Laguerre function. $q \geq 0$, often called scaling factor and $j = 1, 2....$ The Laguerre function $l_j(t)$ is appealing to researcher because of having a simpler form of Laplace transform as

$$\int_0^\infty l_j(t)e^{-st}dt = \sqrt{2q}\frac{(s-q)^{j-1}}{(s+q)^j} \tag{3.2}$$

From equation (3.2), a differential equation can be derived which satisfied by the Laguerre function. Let $L(t) = [l_1(t)\ l_2(t)...l_m(t)]'$ and $L(0) = \sqrt{2q}[11...1]'$ Then the differential equation satisfied by the Laguerre function

$$\dot{L}(t) = A_q L(t) \tag{3.3}$$

where,

$$A_q = \begin{bmatrix} -q & 0 & \dots & 0 & 0 \\ -2q & -q & \dots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ -2q & -2q & \dots & -2q & -q \end{bmatrix}$$

The equation (3.3) yield to a Laguerre function in form of exponential equation of as

$$L(t) = e^{A_q t} L(0) \tag{3.4}$$

For a linear time invariant stable closed loop system, the control sequence for the change in set point, exponentially converges to a constant. Therefore, the control sequence derivative $\dot{u}(t)$ converge to a value of zero, when it is assumed that the closed loop system is stable within each moving horizon window $t_j \leq t \leq t_j + T_P$. It is seen that

$$\int_{t_j}^{t_j+T_P} \dot{u}(t)^2 dt < \infty \tag{3.5}$$

By applying the technique used by Wang[13]. The control sequence derivative can be described by using a Laguerre function as

$$\dot{u}(t) = L(t)^T \kappa \tag{3.6}$$

where, κ is the vector coefficient of orthonormal function $l_j(t)$.

3.5 Predicted Plant Model

It is assume that input is not effecting the output directly. The plant (aircraft system) to be controlled is a multivariable state space system with two input and two output, described in the state space form as

$$\begin{aligned} \dot{x}_s(t) &= A_s x_s(t) + B_s u(t) \\ y(t) &= C_s x_s(t) \end{aligned} \tag{3.7}$$

Let us define an auxiliary variable $H(t) = \dot{x}_s(t)$.
The state space system (equation 3.7) can now be written in an augmented form

$$\dot{x}_a(t) = A_a x_a(t) + B_a u(t)$$

$$y(t) = C_a x_a(t) \tag{3.8}$$

where,

$$x_a(t) = \begin{bmatrix} H(t) \\ y(t) \end{bmatrix} \qquad A_a = \begin{bmatrix} A_s & 0 \\ C_s & 0 \end{bmatrix}$$

$$B_a = \begin{bmatrix} B_s \\ 0 \end{bmatrix} \qquad C_a = \begin{bmatrix} 0 & I \end{bmatrix}$$

It is possible to track the output of the original system using a model predictive control[13]. This only holds when there are no constraints acting on the system.

It is assumed that the state variable $x(t_j)$ is available at the current time t_j. Then at future time $t_j + \tau_t$; $\tau_t > 0$, The predicted state variable $x(t_j + \tau_t)$ is define as

$$x(t_j + \tau_t) = e^{A_a \tau_t} x(t_j) + \int_0^{\tau_t} e^{A_a(\tau_t - \Gamma)} B_a \dot{u}(\Gamma) d\Gamma \tag{3.9}$$

The control signal can be written as $\dot{u}(t) = [\dot{u}_1(t) \ \dot{u}_2(t)]$. The j^{th} control signal $\dot{u}_j(t)$ can be expressed as the orthonormal basis function.

$$\dot{u}_j(t) = L_j(t)^T \kappa_j \tag{3.10}$$

Then the predicted future state at time $t_j + \tau_t$, $x(t_j + \tau_t)$ is

$$x(t_j + \tau_t) = e^{A_a \tau_t} x(t_j) + \phi_j(\tau_t)^T \kappa \tag{3.11}$$

where,

$$\phi_j(\tau_t)^T = \int_0^{\tau_t} e^{A_a(\tau_t - \Gamma)} B_j L_j(\Gamma)^T d\Gamma \tag{3.12}$$

And the plant predicted output can be presented by

$$y(t_j + \tau_t) = C_a x(t_j + \tau_t) \tag{3.13}$$

The convolution operation in equation (3.11) is the major problem in evaluating the prediction. The solution of the convolution integral $\phi(\tau)^T$ can be calculated by satisfying the following linear algebraic equation.

$$A_q\phi(\tau_t)^T - \phi(\tau_t)^T A_q^T = -BL(\tau_t)^T + e^{A_a\tau_t}BL(0)^T \tag{3.14}$$

Obtaining the matrix $\phi(\tau_t)^T$ as shown above, the prediction $x(t_j + \tau_t)$ can be determined and predicted output can be calculated.

3.6 Predictive Control Strategy

To compute the optimal control, a cost function has to be optimized. Let a future set point $r(t_j + \tau_t) = [r_1(t_j + \tau_t)\ r_2(t_j + \tau + t)]$ for $0 \leq \tau_t \leq T_P$ where T_P is the prediction horizon. The cost function can be defined as

$$I = \int_0^{T_P} [r(t_j + \tau_t) - y(t_j + \tau_t)]^T Q[r(t_j + \tau_t) - y(t_j + \tau)]d\tau_t + \int_0^{T_P} \dot{u}(\tau_t)^T R\dot{u}(\tau_t)d\tau_t \tag{3.15}$$

where Q and R are the symmetric weight matrices with $Q \geq 0,\ R \geq 0$.

when the set point is a constant signal, by subtracting $r(t_j)$ from variable $y(t_j + \tau_t)$, the augmented state vector takes the form

$$x(t_j + \tau_t) = \begin{bmatrix} H(t_j + \tau_t) \\ e(t_j + \tau_t) \end{bmatrix}$$

where, $e(t_j + \tau_t) = y(t_j + \tau_t) - r(t_j)$.

By choosing $Q = C^T C$, in conjunction with the augmented model the cost function can be written as

$$I = \int_0^{T_P} [x(t_j + \tau_t)^T Qx(t_j + \tau_t) + \dot{u}(\tau_t)^T R\dot{u}(\tau_t)]d\tau_t \tag{3.16}$$

where, $x(t_j + \tau_t)$ contains the error $e(t_j + \tau_t) = y(t_j + \tau_t) - r(t_j)$ instead of $y(t_j)$.

By exploiting the orthonormal properties of the Laguerre function the cost function can be composed as

$$I = \int_0^{T_P} [x(t_j + \tau_t)^T Qx(t_j + \tau_t)]d\tau_t + \kappa^T R_L\kappa \tag{3.17}$$

Putting the state variable from equation (3.11) in equation (3.17) and the solving it. we get

$$I = [\kappa + F^{-1}Gx(t_j)]^T F[\kappa + F^{-1}Gx(t_j)] + x(t_j)^T \int_0^{T_P} e^{A_a^T \tau_t} Q e^{A_a \tau_t} d\tau_t x(t_j) - x(t_j)^T G^T F^{-1} G x(t_j) \quad (3.18)$$

where,

$$F = \int_o^{T_P} \phi(\tau_t)^T Q \phi(\tau_t) d\tau_t + R_L$$

$$G = \int_o^{T_P} \phi(\tau_t) Q e^{A_a \tau_t} d\tau$$

The minimum of the cost function (equation 3.18) without hard constraints on variable is given by the least square solution.

$$\kappa = -F^{-1}Gx(t_j) \quad (3.19)$$

The derivation of the control input $\dot{u}(t)$ can now be computed from equations (3.10) and (3.19) as

$$\dot{u}(t_j) = -L_j(\tau_t)F^{-1}Gx(t_j) \quad (3.20)$$

or

$$\dot{u}(t_j) = -k_{mpc}x(t_j)$$

where, $k_{mpc} = L_j(\tau_t)F^{-1}G$ is the model predictive controller gain matrix.

By integrating the equation (3.20) we will get our control law. Because of the cost function (equation 3.18) is a quadratic function, it is easy to put hard constraints on the states, outputs, and control variables of the system.

3.7 Model predictive control for the aircraft

Before applying the model predictive control strategy to the aircraft model, the aircraft system is stable but unable to achieve good transient performances to the change in various inputs such as elevator,aileron and rudder, which is undesirable see figure. For the aircraft system, not having good transient performances leads to instability of the system.

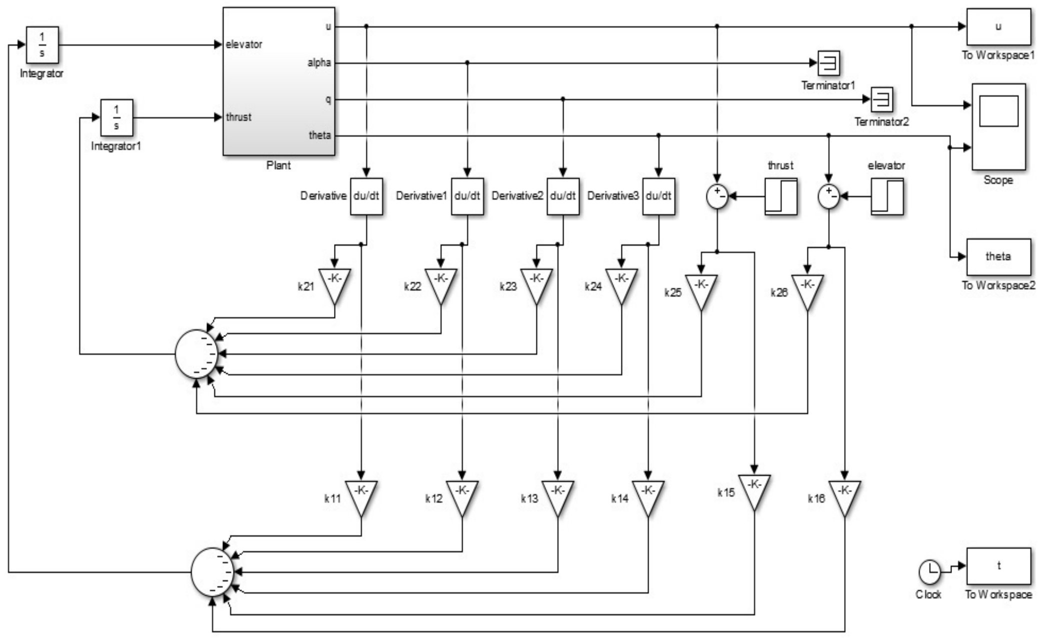

Figure 3.3: Simulink model of Continuous Time Model Predictive Control applied to Longitude Mode of the Aircraft

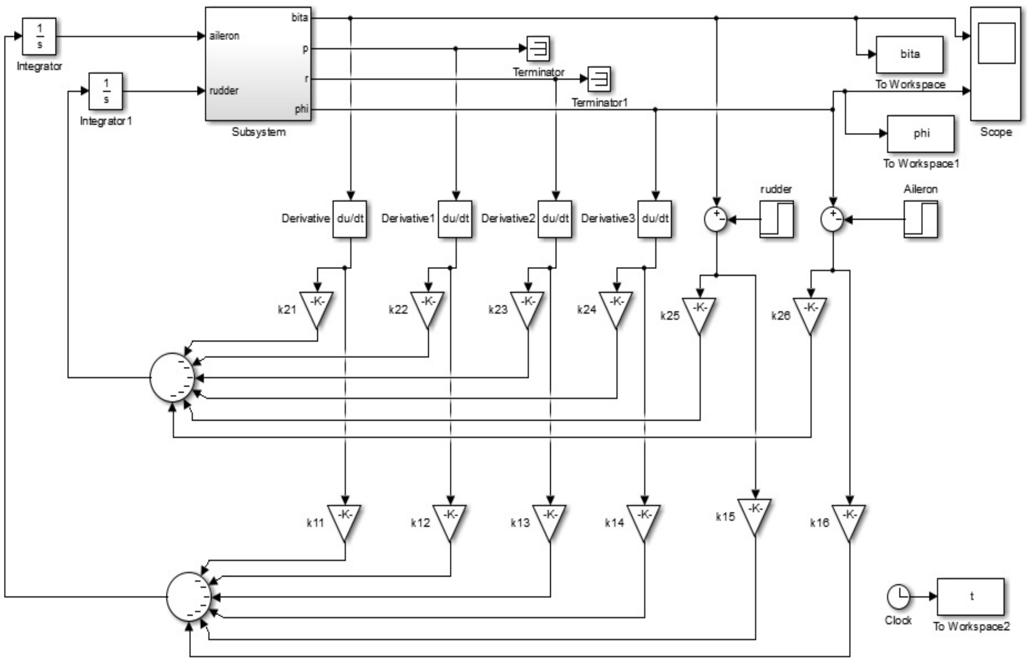

Figure 3.4: Simulink model of Continuous Time Model Predictive Control applied to Lateral Mode of the Aircraft

Above discussed model predictive control strategy is applied to the simulated mathematical model of the aircraft Boeing-767. Simulation were pursuit utilizing Matlab / Simulink to understand the effect of model predictive control strategy on the aircraft system.

In the MPC design for the aircraft we are changing the input actuator as elevator, aileron and rudder and seeing the effect in the transient performances of the pitch angle, anlge of sideslip and the angle of roll.

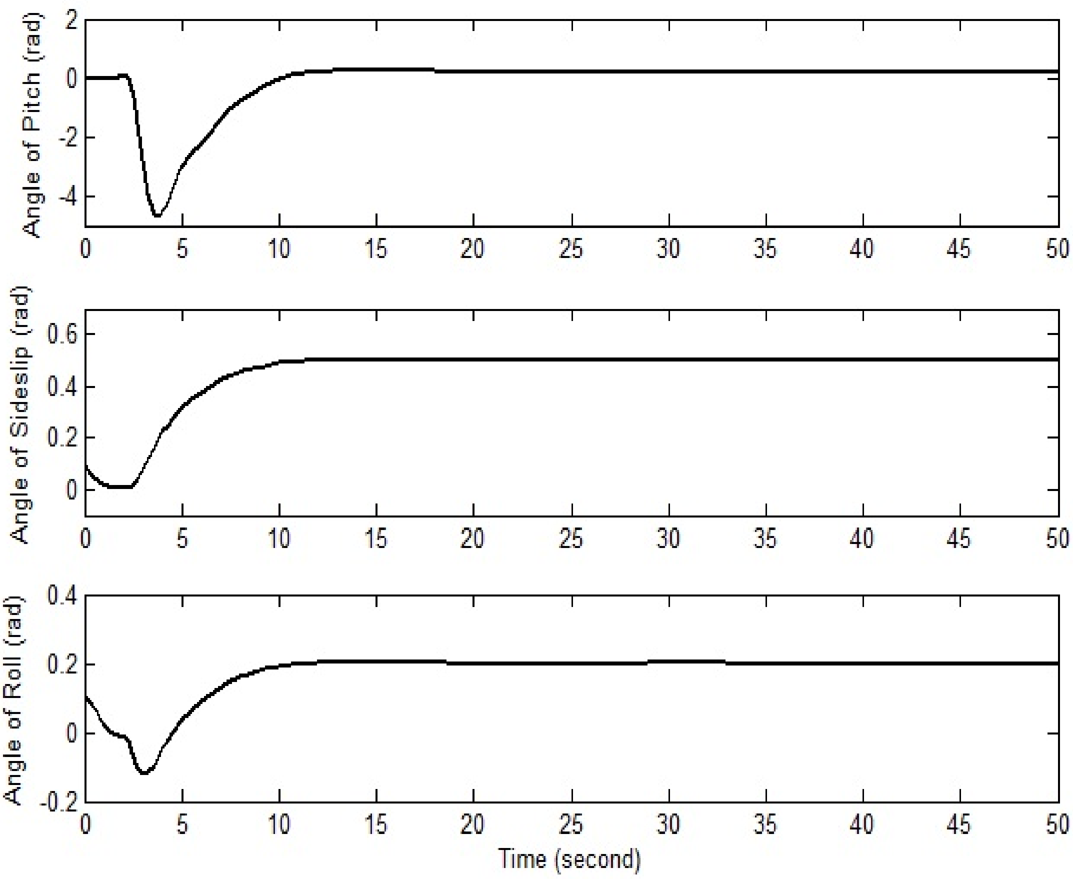

Figure 3.5: Step response of Angle of Pitch, Sideslip and Roll utilizing Model Predictive Control Strategy

After applying the MPC to the aircraft control system, the poles of the overall system shifted towards the left of the s-plane. Therefore, the stability of the system is increased as well as the transient performances of the system now reduces to small value as compared to the previous case.

Figure 3.5 shows the improved transient performance of the aircraft control system. From figure, it is clear that the application of the MPC to the aircraft control system is very helpful to achieve the desired performances and tracking the references or the regulation of the system.

Chapter 4

Modeling of an Aircraft Engine

Chapter 4

Modeling of the Aircraft Engine

An engine of an aircraft constitute a complex system, which obliging efficient checking for guaranteed flight safety and time to time maintenance. In order to monitoring the aircraft engine, a mathematical model of aircraft engine is to be design in Matlab / Simulink. In designing the mathematical model of double spool turbofan engine we focus on fuel flow rate, exhaust nozzle opening and spool speeds, because of their interesting properties, resulted from theoretical and experimental studies.

Modern aircraft engines, mainly the fighter aircraft engines must have high level of thrust, low transient response and maneuverability. For a higher level of thrust, compressors pressure ratio and temperature of combustor must be high. For high values of compressor pressure ratio, the compressor must be split in two or more parts. A gas turbine is coupled with each compressor unit i.e. turbo-compressor shaft or spools. In other words, To achieve high level of thrust and high compressor ratio a simple engine is converted to a multi-shaft engine. Each shaft rotates at different speed.

4.1 Principle of Aircraft Propulsion

Fundamental rule in a airplane motor is to quicken a mass of fluid in the heading inverse to movement and along these lines moving the flying machine forward by the push generated. The motor sucks air in at the front with a fan. A compressor raises the weight of the air. The compressor is comprised of fans with numerous edges and joined to a pole. The edges pack the air. The compacted air is then showered with fuel and an electric sparkle lights the blend in the combustor. The smoldering gasses grow and impact out through the spout, at the back of the motor. As the planes of gas shoot in reverse, the motor and the air ship are push forward.

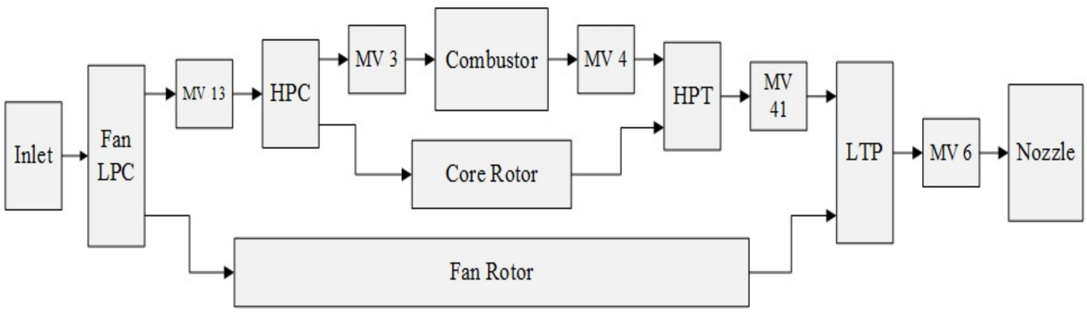

Figure 4.1: Schematic diagram of Two Shaft Turbofan Engine

4.2 System Description

At point H surrounding air goes from free stream to the flight admission driving edge at 1 and the air quickens from free stream if the motor is static, it then diffuses at point 2_1 in the fight allow before going through the motor admission to the compressor face with a little misfortune altogether pressure.

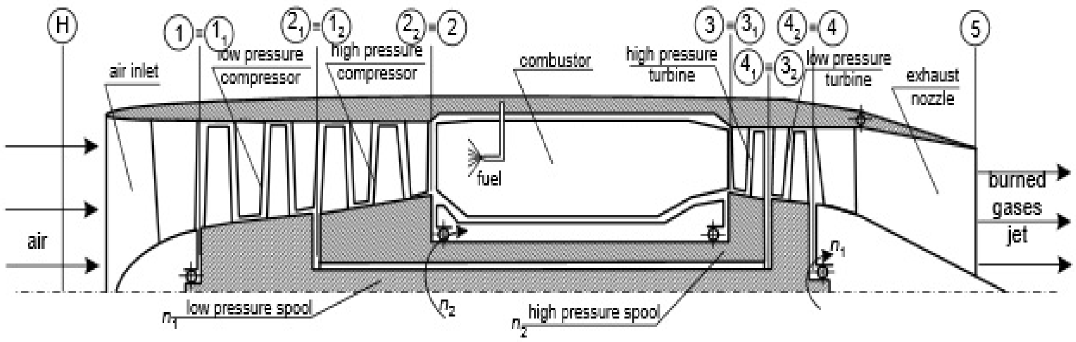

Figure 4.2: Two Shaft Single Jet Engine

The compressor then increments both the weight and temperature of the gas. Work info is obliged to accomplish the weight proportion; the related temperature rise relies on upon the efficiency of the compressor. The compressor exit diffuser at point 2 passes the air to the combustor. Here, fuel is infused and smoldered to raise way out gas temperature at point 3. The diffuser and combustor both force a little aggregate weight misfortune. The hot, high weight gas is then extended through the turbine where work is separated to deliver shaft power; both temperature and weight are lessened. The pole force is that needed to drive the compressor what's more, any motor helpers. On leaving the turbine at point 5, the gas is still at a weight ordinarily in any event twice that of encompassing. This outcomes from the higher channel temperature to the turbine.

4.3 System Parameter

As control parameters (inputs) for a single-jet double spool engine, only one input can be identified: the fuel flow rate Q_f (which is the most important control parameter). The controlled parameters are, obviously, the shafts speeds (n_l and n_h) meanwhile, the combustors temperature (T_4) is a limited controlled parameter, its limitation being realized through the fuel flow-rate control. Therefore,

$$States\ variable\ x = \begin{bmatrix} n_l \\ n_h \\ T_4 \end{bmatrix} = \begin{bmatrix} speed\ of\ fan\ shaft \\ speed\ of\ core\ shaft \\ temperatura\ at\ HPT\ inlet \end{bmatrix}$$

$$Control\ variable\ u = [Q_f] = [rateoffuelflow]$$

4.4 System Dynamics

The first venture in building up this engine simulaiton is the definition of an analytical model[2]. This model, in comparison structure, speaks to the useful relations that exist between the engine variables, for example, weights, temperatures, and gas flow rates. The engine model ought to be fit for precisely foreseeing both the enduring state and element execution of the engine.

Shafts rate are straightforwardly connected with mass course through the motor and the push, which is the principle yield to be controlled by the impetus control system.If n_l and n_h are the fan shaft speed and center shaft speed separately then as indicated by Newton's law for pivoting masses connected to each shaft.

$$\begin{aligned} \dot{n}_l &= f_l(n_l, n_h, Q_f, T_4) \\ \dot{n}_h &= f_h(n_l, n_h, Q_f, T_4) \end{aligned} \tag{4.1}$$

where f_l and f_h are the net torque conveyed by the low pressure turbine and high pressure turbine respectively after normalizing by mass moment of inertia of shaft congregations.

Because of complicated geometry of the motor segment and the intricacy of gas stream, the mathematical expression for f_l and f_h are impractical. However, for model generation and simulation, equation (4.1) is linearize to incorporate data about torque f_l and f_h through their partial derivatives.

At the point when consistent estimation of Q_f is connected alongside settled arrangement of parameter for f_l and f_h, the motor spans to a steady state operating point with comparing to steady estimations of pace of core shaft and fan shaft. For these condition, small signal linearization yield the model

$$\begin{aligned} \dot{x} &= Ax + Bu \\ y &= cx \end{aligned} \tag{4.2}$$

where,

$$x = \begin{bmatrix} n_l \\ n_h \\ T_4 \end{bmatrix} \qquad A = \begin{bmatrix} -312.003 & 0 & -689.27 \\ 0 & -1879.2 & -6305 \\ 0 & 0 & -3.371 \end{bmatrix}$$

$$B = \begin{bmatrix} 0 \\ 0 \\ 5.91e^7 \end{bmatrix} \qquad C = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 3.74 \\ 1 & 1 & 3.74] \end{bmatrix}$$

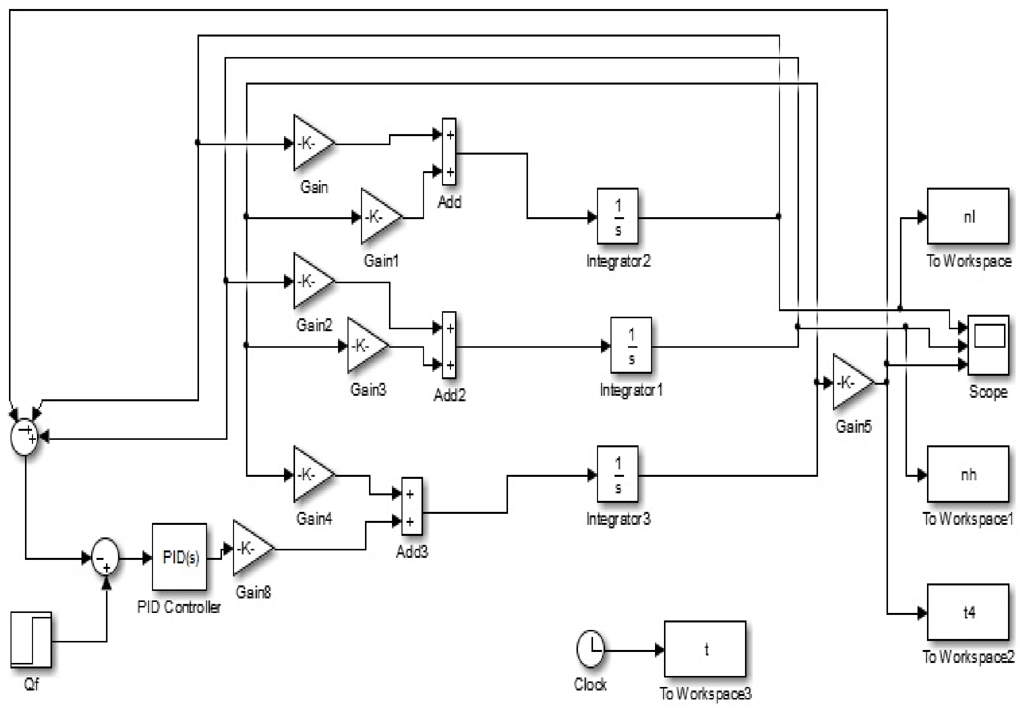

Figure 4.3: Simulink model of Two Shaft Turbofan Engine

The output measured incorporate n_l, n_h and overall pressure ratio(OPR). An invented yield (f_y) including a mix of all the three state is considered in this proposition to guarantee the observability of the system. A basic PID controller is executed for the nonlinear framework to manage the center shaft speed (n_h) to a predefined set point.

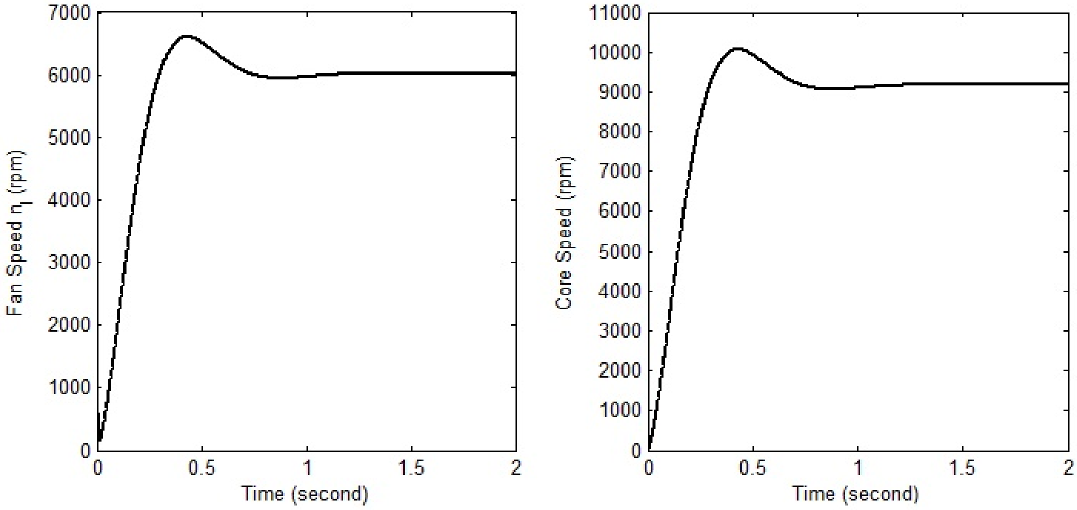

Figure 4.4: Shaft Speed of Simulated Two Shaft Turbofan Engine

The speeds of the fan shaft and the core shaft appears as shown in the Figure 4.4. The speeds of both the propeller shaft and the core are not inherently steady, they reach their respective steady state after a certain fractional time lapse. However, the core shaft speed was brought to a particular set point of 9000 rpm with an intuitive implementation of PID controller as per requirements and then with this set point the fault detection of the aircraft was performed.

Chapter 5

Fault Detection & Isolation Strategy

Chapter 5

Fault Detection and Isolation Strategy

A fault diagnosis scheme for aircraft engine signifies the shortcoming location and its seclusion. Issue identification and separation plan assumes a pivotal part in upgrading the well being, unwavering quality and diminishing the working expense of aircraft propulsion system. Then again, accomplishing the issue identification and separation plan with high unwavering quality is a testing issue. For this reason, different methodologies have been proposed.

Some of the approaches used in fault detection and isolation scheme are Kalman filtering, neural networks and hybrid diagnosis. Numerous current shortcoming identification and seclusion plan are in light of the suspicion that the system shows straight conduct in the area of the enduring state working focuses. Consequently, linearization based symptomatic plan are frequently utilized. Since the elements of the air ship motor are profoundly nonlinear, therefore traditional linear model Kalman filter method, subjected to linear uncertainties is used.

5.1 Fault Detection and Isolation Logic

To outline the issue location and segregation plan for the flying machine motor a shortcoming discovery estimator is utilized to screen the event of the flaw and a bank of Kalman channels are utilized to focus the specific deficiency sort. The methodology utilized model based flaw recognition is made out of two stages. To start with produce the lingering sign from the sensor estimation and their Kalman channel assessed qualities and second contrast the residual with threshold to make shortcoming identification.

The Kalman Filter is an estimator for the straight quadratic issue, which is the issue of evaluating the immediate condition of a direct element system annoyed by repetitive noise by utilizing estimations straightly identified with the state however defiled by background noise. To control a dynamic framework, it is crucial to know the whole condition of the framework. For applications where it is not generally conceivable to quantify each variable that requirements to be controlled, the Kalman channel gives an intends to gathering the missing data from indirect (and noisy) estimations.

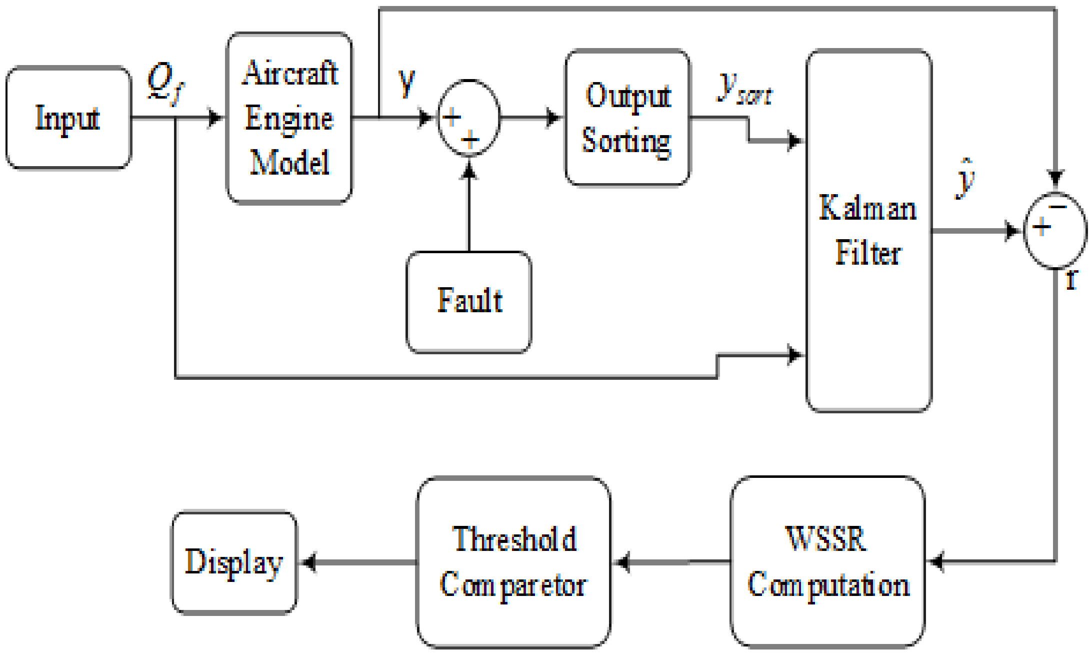

Figure 5.1: Block Diagram of the Fault Detection and Isolation Strategy

With the Engine Simulation display that was produced, the model-based deficiency identification methodology is executed, which comprises of a bank of Kalman channels that is utilized for sensor flaw discovery and detachment. Each

Kalman channel is intended for identifying a particular sensor shortcoming. If a sensor flaw does happen, all channels with the exception of the one utilizing the right theory will deliver vast estimation lapses, subsequently disengaging the sensor that has fizzled.

A linear model of the engine simulated model is represented by the following state space equations

$$\dot{x}_s = A_s x_s + B_s u + \omega$$

$$y_s = C_s x + D_s u + \nu \tag{5.1}$$

where, ω and ν are the process and sensor noise respectively, the are both assumed to be white Gaussian noise. Their covariance matrices are

$$E[\omega(t_t)] = 0$$

$$E[\nu(t_t)] = 0$$

$$E[\omega(t_t + \tau_t)\omega^T(t_t)] = Q\delta(\tau_t)$$

$$E[\nu(t_t + \tau_t)\nu^T(t_t)] = R\delta(\tau_t)$$

The estimated state vector $\hat{x}_s$, sensor measurement $\hat{y}_s$ and the kalman gain matrix K can be calculated as

$$\dot{\hat{x}}_s = A_s \hat{x}_s + B_s u + K(y_s - \hat{y}_s)$$

$$\hat{y}_s = C_s \hat{x}_s$$

$$K = P C_s^T R^{-1} \tag{5.2}$$

where, innovation matrix P is calculated by utilizing the linear Riccati equation.

5.2 Identification of Sensor Fault

A bank of "n" Kalman Filter (n is the number of yields) is utilized to execute the sensor flaw recognition logic. As said, the control info and a subset of the sensor yield estimations are encouraged to each of the "n" Kalman filter. The sensor that is not utilized by a specific channel is the one being checked by that channel for flaw location. Thus every channel assesses the expanded state vector utilizing (n 1) sensors. Consequently if sensor "i" is defective, all channels will utilize a debased estimation, aside from channel "i". Channel "i" will accordingly have the capacity to gauge the expanded state vector from issue free sensor estimations, though the assessments of the remaining channels will be misshaped by the flaw in sensor "i". When the expanded state vector appraisal is found, the sensor estimations can be assessed utilizing the Kalman Filter arrangement of mathematical statement. For each filter, the residual vector is generated

$$r^j = {y_s}^j - \hat{y}_s^j$$

Consequently with the recreated motor model each of the 4 Kalman Filters gauges the yield utilizing 3 sensor estimations (flawed) and the control data. For this situation, since the sensor estimation 2 is flawed, all channels with the exception of channel 2 will utilize an adulterated estimation. Channel 2 will hence have the capacity to gauge the motor yields from issue free sensor estimations, while the yield appraisals of the remaining channels (i.e., channels 1, 3 and 4) will be misshaped by the deficiency in sensor 2.

As we got the residual, the Weighted Sum of Squares Residual (WSSR) for each Kalman filter can be calculated as

$$W^j = V^j {r^j}^T \Sigma^{-1} r^j$$

It contains two hypotheses as

- System operate normally if, Threshold value for a particular sensor is greater then the weighted sum of squares residual of that sensor.
- Fault in the system if, Threshold value for a particular sensor is less then the weighted sum of squares residual of that sensor.

Using above two hypotheses we can identify and seclude the presence of faults and the false alarm.

5.3 Fault Identification and Isolation for the Modeled Aircraft Engine

Above discussed fault identification and seclusion strategy utilizing a bank of Kalman Filter is implemented on the simulated mathematical model of aircraft engine develop in previous chapte, with a fault in the core shaft. A fault is injected in the form of step signal with magnitude of 5000 at a time of 0.5 sec.

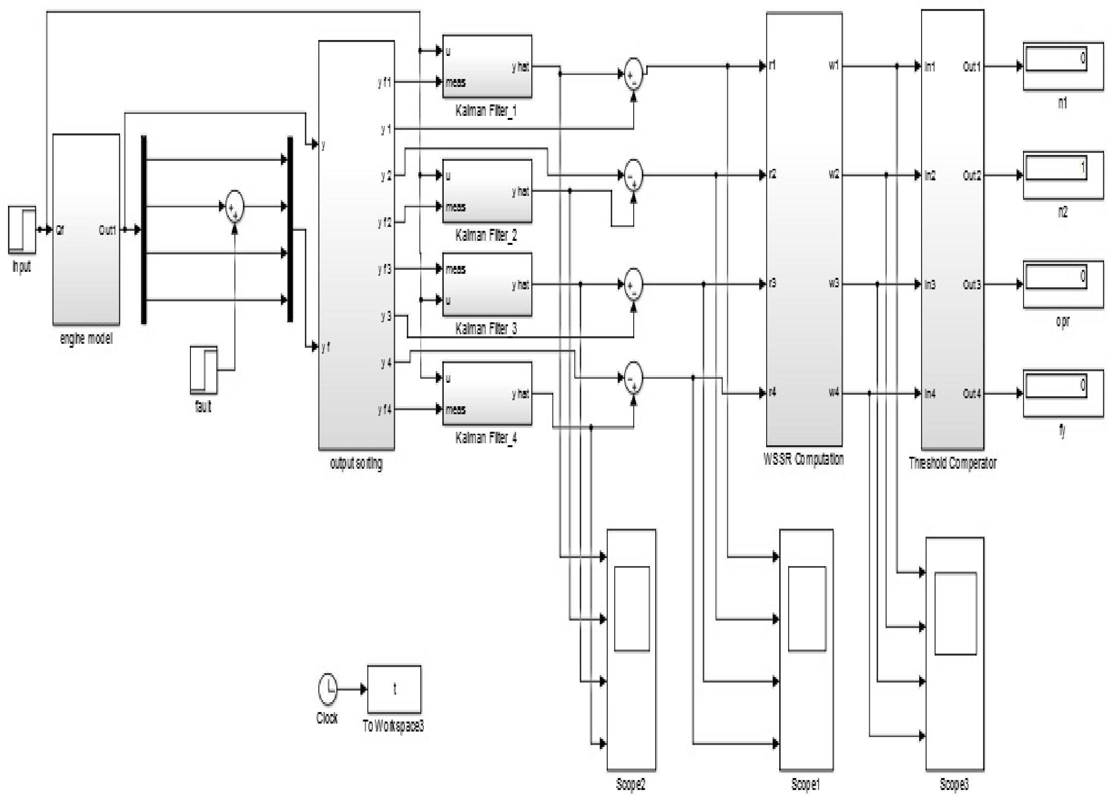

Figure 5.2: Simulink Model of the Fault Detection and Isolation Strategy applied to the Aircraft Engine

5.3.1 No Sensor Fault

The estimated values of the sensor output for all the Kalman filter are shown in figure below

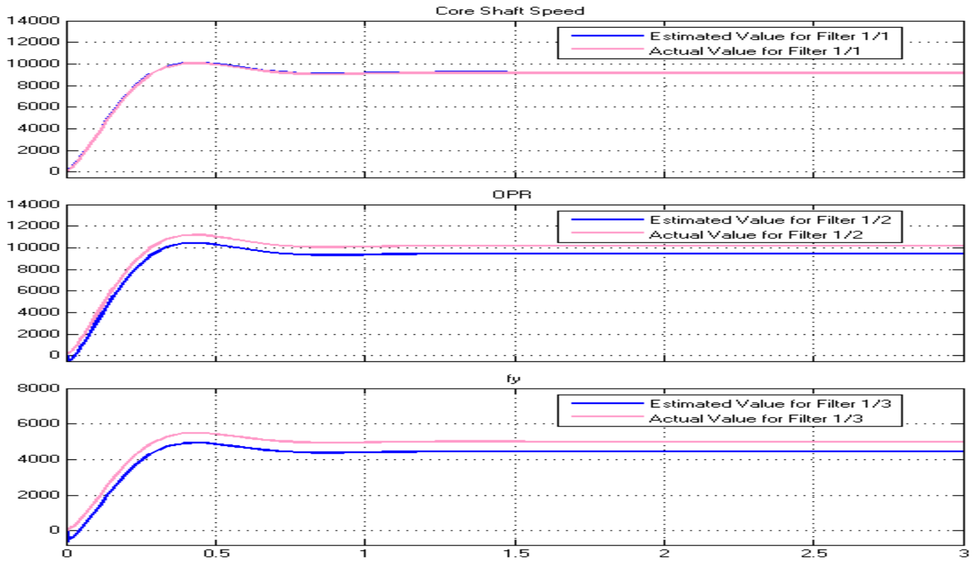

Figure 5.3: Estimated Output of Kalman Filter 1

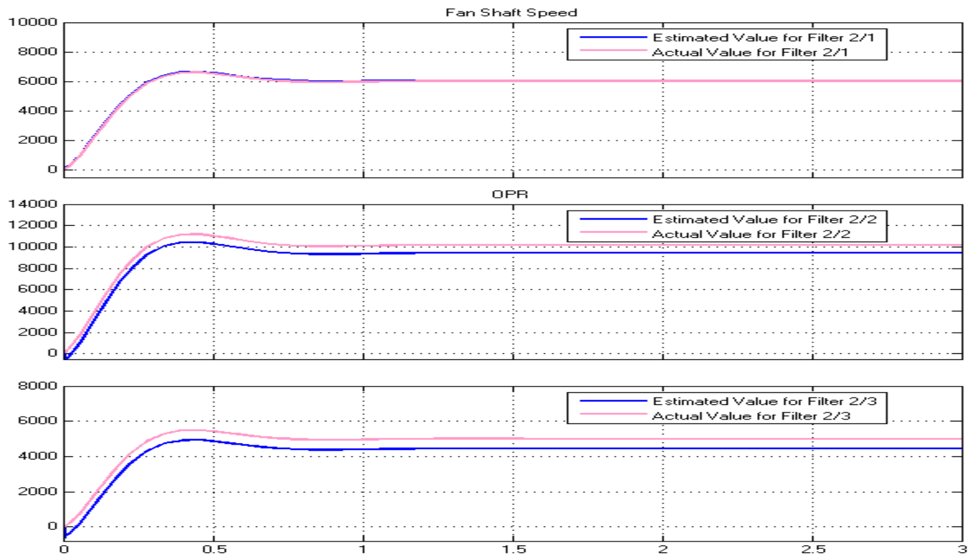

Figure 5.4: Estimated Output of Kalman Filter 2

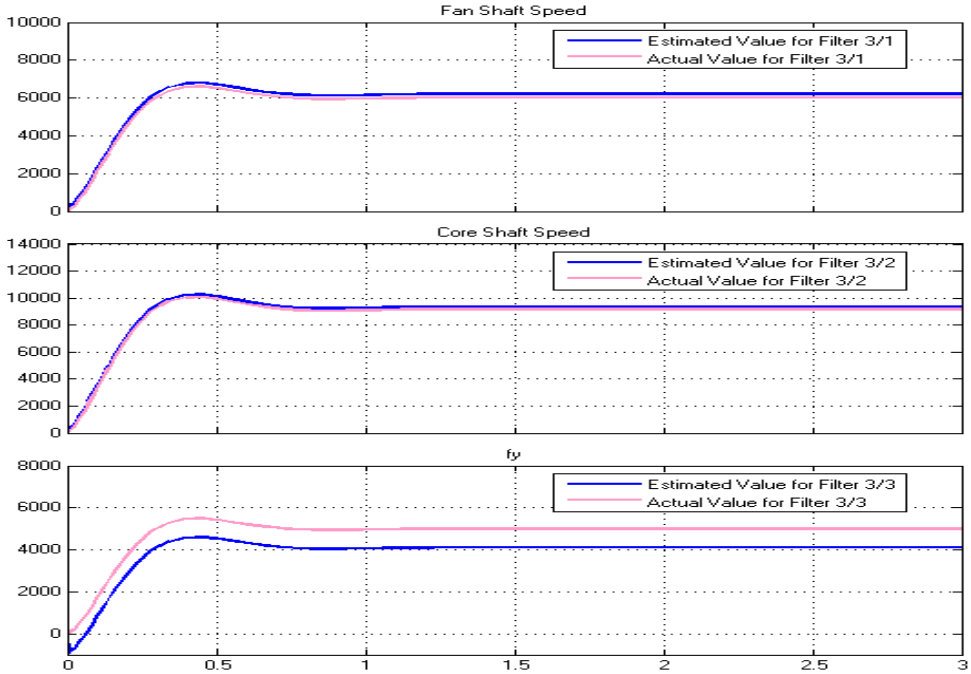

Figure 5.5: Estimated Output of Kalman Filter 3

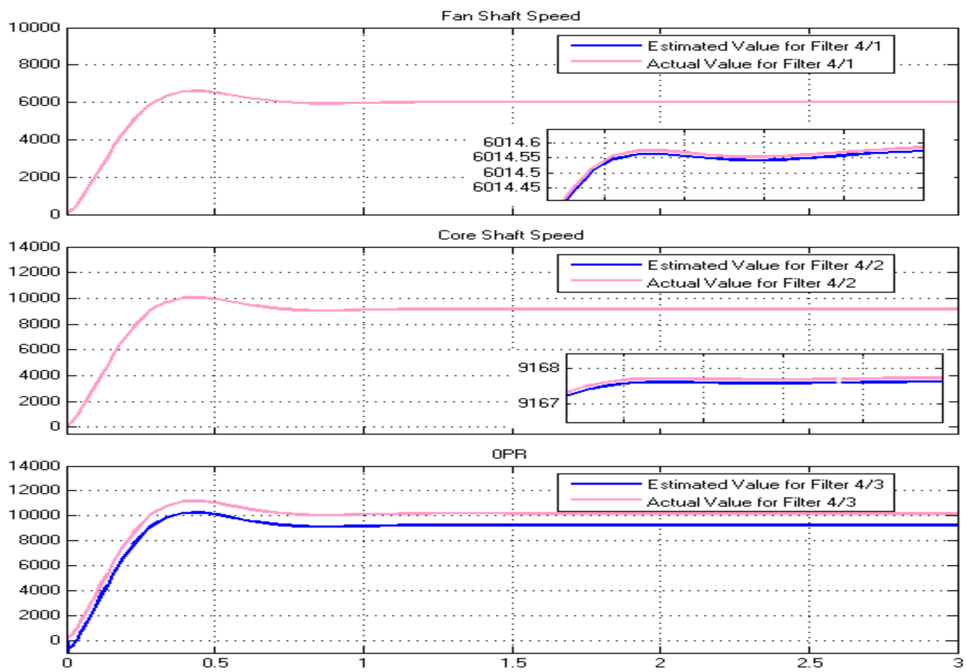

Figure 5.6: Estimated Output of Kalman Filter 4

5.3.2 Fault in the Core Shaft Speed Measurement Sensor

The estimated values of the sensor output for all the Kalman filter are shown in figure 5.7, 5.8, 5.9 and 5.10. The residual vectors and WSSR for the 4 Kalman filters are shown in Figures 5.11 and 5.12 respectively. We note that the estimated outputs for Kalman Filter 1,3 and 4 have higher error than Kalman Filter 2. WSSR plots for Kalman Filter 1,3 and 4 are also seen to be high whereas the WSSR for the Kalman Filter 2 is very less.

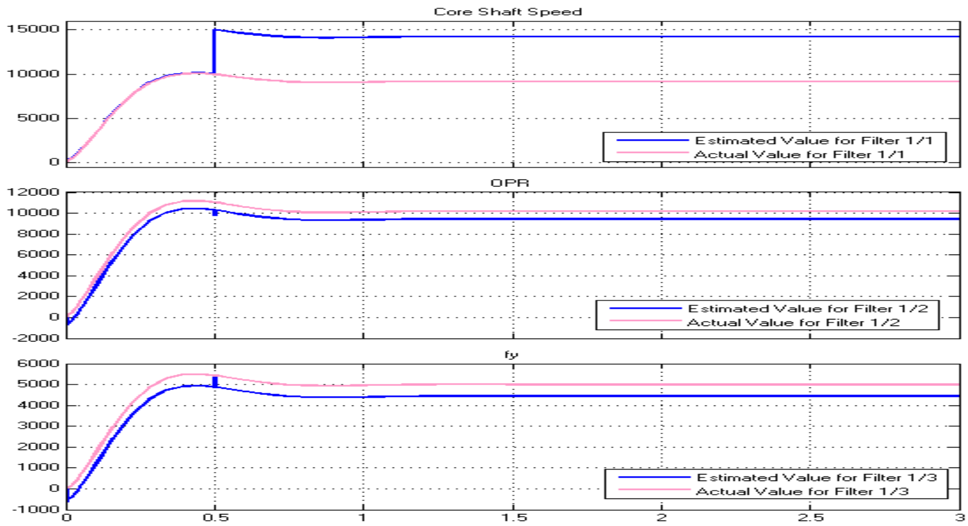

Figure 5.7: Estimated Output of Kalman Filter 1

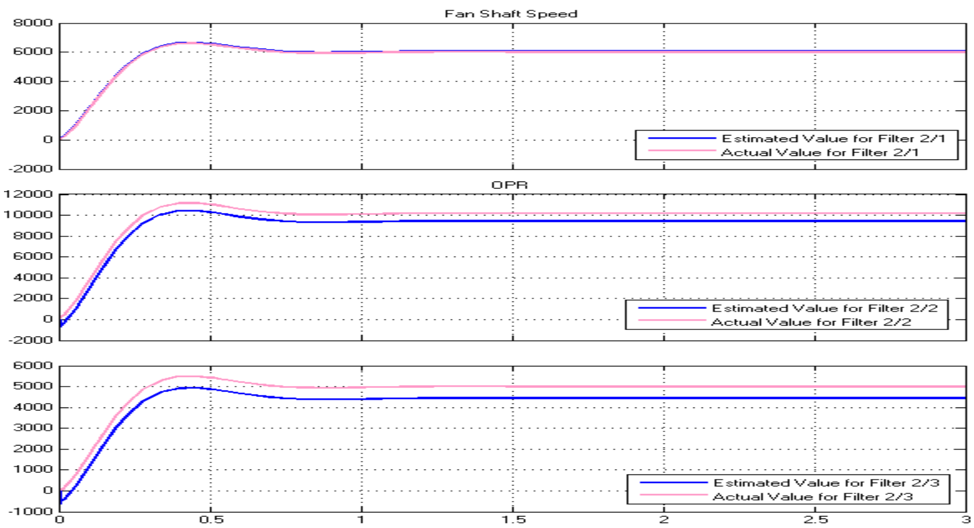

Figure 5.8: Estimated Output of Kalman Filter 2

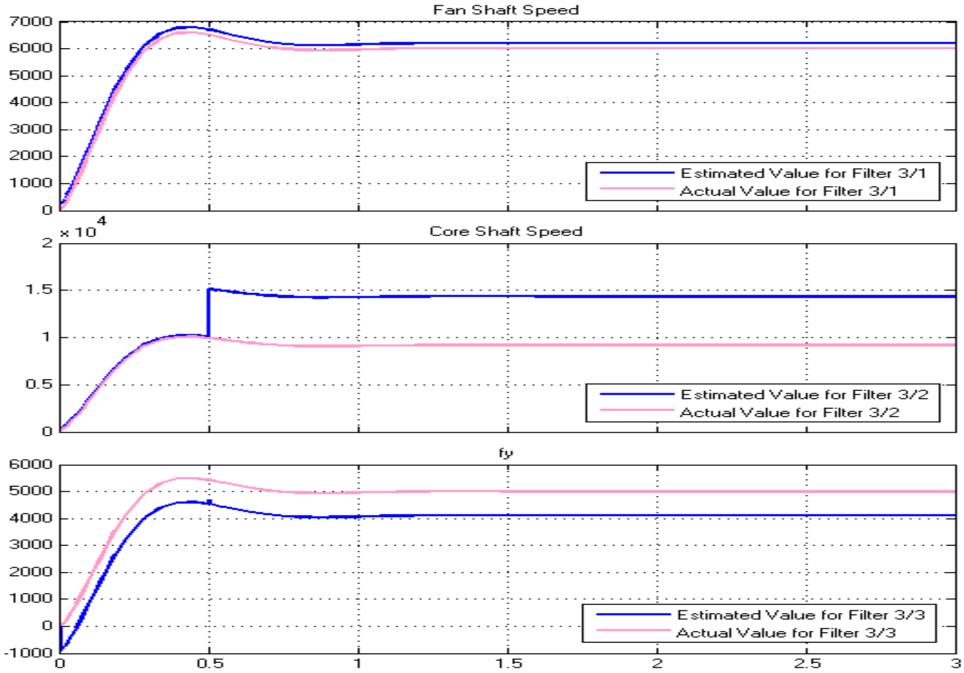

Figure 5.9: Estimated Output of Kalman Filter 3

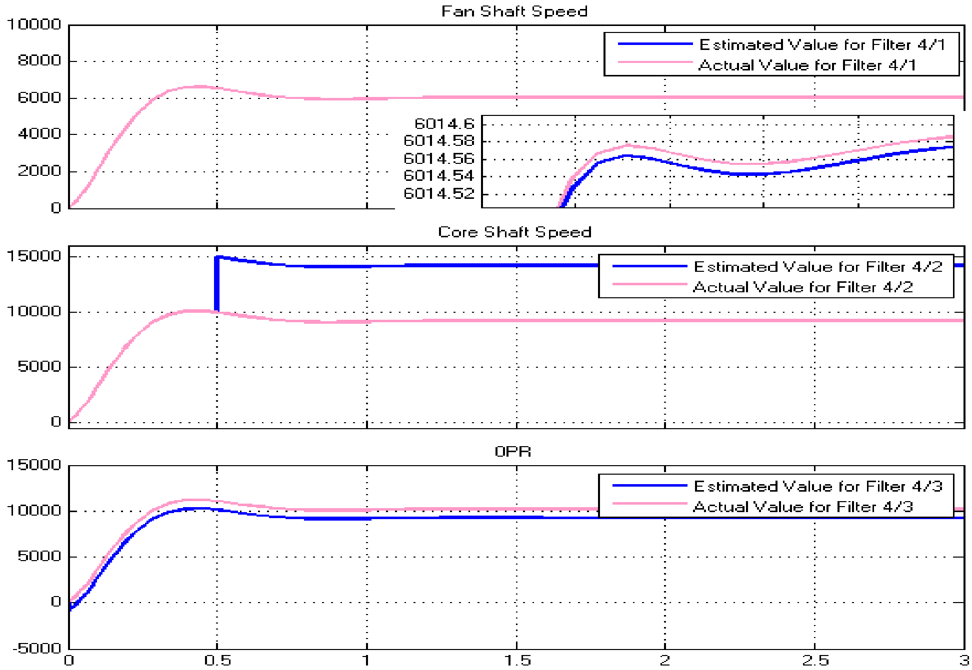

Figure 5.10: Estimated Output of Kalman Filter 4

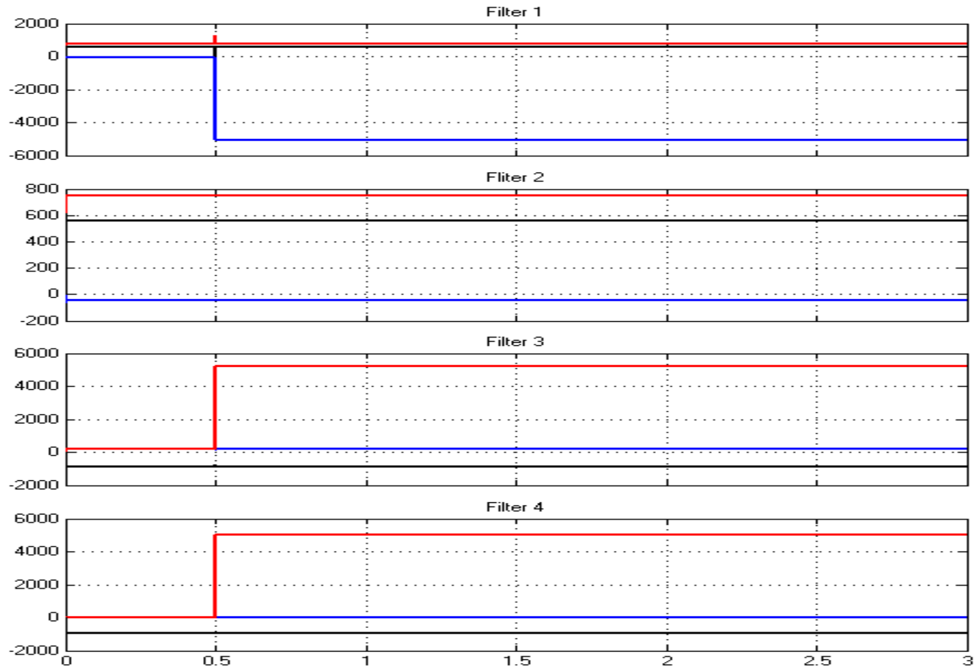

Figure 5.11: Residual Vector for all Kalman Filters

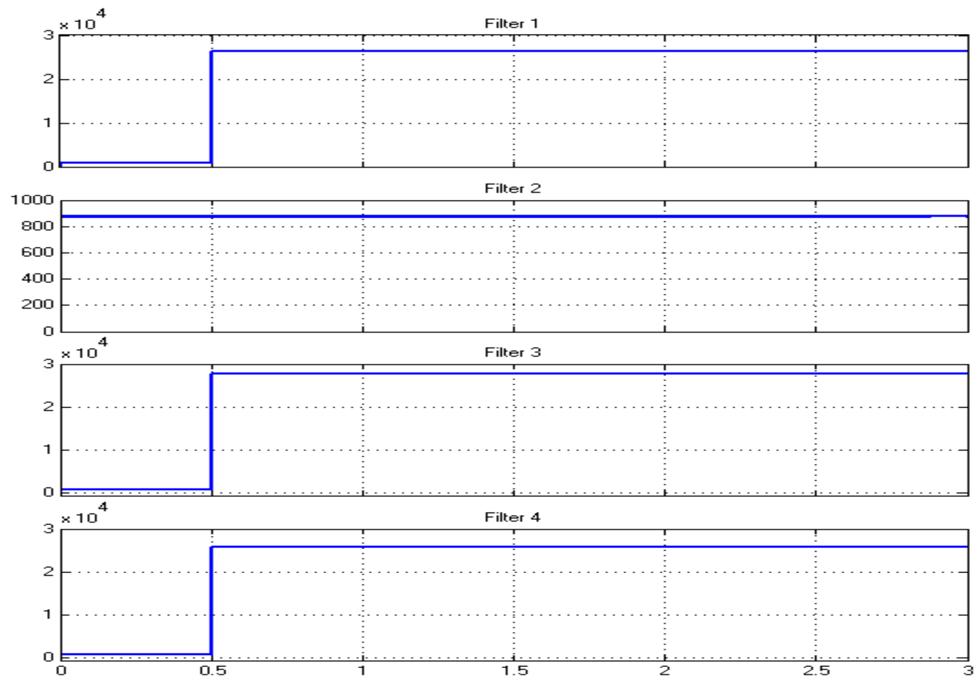

Figure 5.12: WSSR for all the Kalman Filter

5.3.3 Fault in the Fan Shaft Speed Measurement Sensor

A fault is injected in the form of step signal with magnitude of 5000 at a time of 0.5 sec. The residual vectors and WSSR for the 4 Kalman filters are shown in Figures 5.13 and 5.14 respectively.

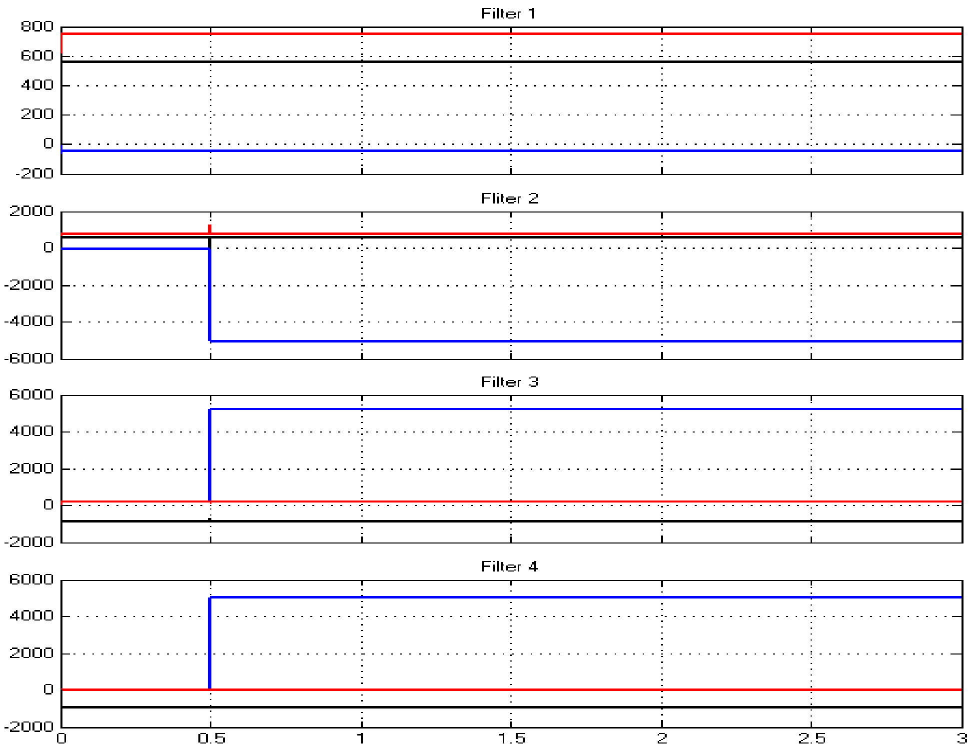

Figure 5.13: Residual Vector for all Kalman Filters when Faulty Fan Shaft Speed Measurement Sensor

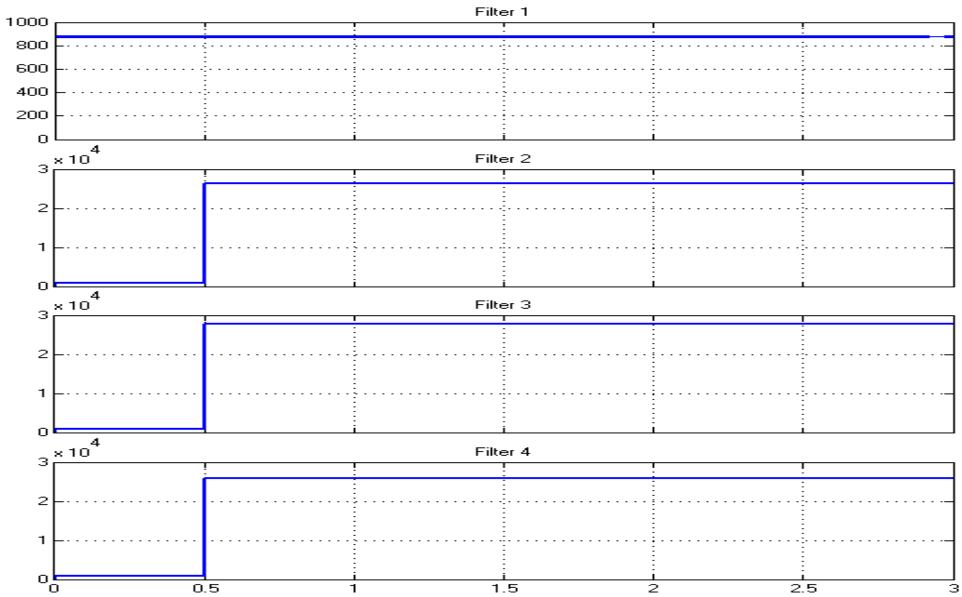

Figure 5.14: WSSR for all the Kalman Filter when Faulty Fan Shaft Speed Measurement Sensor

We note that the estimated outputs for Kalman Filter 1,3 and 4 have higher error than Kalman Filter 2. WSSR plots for Kalman Filter 1,3 and 4 are also seen to be high whereas the WSSR for the Kalman Filter 2 is very less.

Chapter 6

Conclusions &
Scope for the Future Work

Chapter 6

Conclusion and Scope for Future Work

6.1 Conclusion

A model of an aircraft system has been designed in an efficient way. The model of Pitch, Roll and Sideslip control of the aircraft is very helpful in developing a control strategy for actual system. Pitch, Roll and Sideslip control of an aircraft is a system which require a controller to maintain the angle at its desired value. This can be achieved by reducing the error signal, which is the difference between output signal and desired signal. The control approach of the Model Predictive Controller is capable of controlling the Pitch, Roll and Sideslip angle of the aircraft system. Simulation results show that Model Predictive controller give better performances.

Futher, this thesis focuses on an aircraft engine system, which is modeled utilizing Matlab / Simulink to ensure the identification and seclusion of the faulty sensor outputs. A fault identification and seclusion strategy, utilizing a bank of Kalman Filters, has been developed. The simulation result obtained envisages that the fault detection and isolation strategy developed utilizing the bank of Kalman Filter has been able to identify and isolate the faulty sensor output in the aircraft engine system.

6.2 Scope for Future Work

For advance work, effort can be devoted in designing the more robust control techniques for the control of the angles of roll, pitch and sideslip. Further, effort can be made in developing the fault identification and seclusion strategy for the actuator of the aircraft engine system utilizing the robust Kalman filter.

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